Analysis of Heavy-Duty Vehicle Sales Impacts Due to New Regulation

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Assessment and Standards Division
Office of Transportation and Air Quality
U.S. Environmental Protection Agency

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Table of Contents

Table of Figures

Table of Tables

Acronyms and Abbreviations

Acronym	Definition
ATA	American Trucking Association
ATRI	American Transportation Research Institute
BEA	U.S. Bureau of Economic Analysis
BLS	U.S. Bureau of Labor Statistics
CARB	California Air Resources Board
CFS	Commodity Flow Survey
CO	Carbon monoxide
CO_2	Carbon dioxide
DOT	United States Department of Transportation
EGR	Exhaust Gas Recirculation
EIA	United States Energy Information Agency
EMFAC	CARB Emission Factors Database
EPA	United States Environmental Protection Agency
FAF	Freight Analysis Framework
FHWA	United States Department of Transportation Federal Highway Administration
g/bhp-hr	Grams per brake horsepower hour
GAO	U.S. General Accounting Office
GDP	Gross domestic product
GHG	Greenhouse gas
GVWR	Gross vehicle weight rating
HC	Hydrocarbon
HDV	Heavy-duty vehicle
HHDV	Heavy Heavy Duty Vehicle
IMO	International Maritime Organization
LIBOR	London Interbank Offer Rate
LTL	Less than Truckload
MHDV	Medium Heavy Duty Vehicle
MOBILE	EPA model predecessor to MOVES
MOVES	MOtor Vehicle Emission Simulator model
MY	Model year
NAS	National Academies of Sciences, Engineering, and Medicine
NHTSA	National Highway Transportation Safety Administration

NMHC	Non-Methane Hydrocarbons
NOx	Oxides of nitrogen
NPV	Net present value
O+M	Operations and maintenance
OECD	Organisation for Economic Co-operation and Development
OEM	Original Equipment Manufacturer
PED	Price elasticity of demand
PM	Particulate matter
PPI	Producer price index
PPI-Trucks	PPI for Trucks and Transit buses GVWR 33,000lbs +
PUM	Public Use Microdata
RIA	Regulatory Impact Analysis
ROA	Return on Assets
SCR	Selective Catalytic Reduction
SCTG	Standard Classification of Transported Goods
TALS	Temporally Adjusted Low-buy Sales rate
TAPS	Temporally Adjusted Pre-buy Sales rate
TL	Truckload
TSA	Transportation Satellite Accounts
UC	University of California
VMT	Vehicle miles traveled
XED	Cross-price elasticity of demand

Executive Summary

Heavy duty vehicle activity is a major source of criteria pollutants in the transportation sector, contributing 35% more particulate matter emissions than light duty vehicles in the United States. The federal government has implemented a series of policies aimed at reducing pollution from heavy-duty vehicles which have cut particulate matter and nitrogen oxide emissions by 90% on a per unit activity basis since 1997. These regulations have led to billions of dollars in estimated health and environmental benefits, but do not come without cost.

This study explores impacts of these regulations for heavy-duty vehicle sales in Classes 6-8, specifically looking for evidence of increases in purchasers in advance of the standards (pre-buy) and reductions afterwards (low-buy). Using sales data and time series econometric methods, this work finds some evidence for Class 8 vehicles of short-term pre-buy and low-buy behaviors (typically less than 8 months) around national-level air quality regulations, with a focus on NOx standards, as well as possible class-shifting; it does not find such evidence for Classes 6 and 7. Pre-buy and low-buy behaviors effectively reduce the effectiveness of proposed regulations, as fleets purchase more vehicles than they normally might prior to the regulation in order to avoid having to pay higher prices for regulation-compliant vehicles after the regulation goes into effect. As such, the effect of the regulation is tempered as the vehicles purchased just prior to regulations persist in the fleet long after the regulation goes into effect.

Small, short lived pre-buy effects were observed for Class 8 vehicles prior to the 2010 and 2014 regulations, though the 2014 pre-buy period was only one month. We observe low-buy in Class 8 sales for the 2004, 2007, and 2010 regulations, with the 2007 low-buy being the strongest and most persistent, leading to a ~15% decrease in monthly Class 8 sales for the period 6 months post-regulation. Low-buy and pre-buy effects were generally short-lived and were observed to diminish towards zero. In the case of the 2010 regulations, the pre-buy prior to regulation going into effect and low-buy post-regulation are on the same order of magnitude and duration, and together reduce the effectiveness of the regulation. In contrast, Class 7 showed some cases of reduced sales before the standards – the opposite of pre-buy – and limited statistical evidence of increases in purchases after the standards. Limited statistically significant effects were found for Class 6, with the overall explanatory power of the model being lower compared to Class 7 and 8 analysis.

We extend this analysis to explore the effect of predicted regulatory cost on pre-buy and low-buy behavior, with mixed evidence supporting greater pre-buy and low-buy effects with greater anticipated cost.

This study also identifies possible indicators of class shifting, which has not been previously discussed in the literature. We find evidence supporting conditions for possible class-shifting between Class 8 and 7 vehicles around the 2004 and 2010 regulations. In 2004 we see a small but significant increase in the ratio of Class 8 to Class 7 vehicles, but no significant increase in Class 8 sales on their own. This finding, taken together with a statistically significant observed decrease in Class 7 sales prior to regulation, are indicative of potential class shifting occurring ahead of the 2004 regulations. In 2010 we again see a statistically significant increase in the ratio of Class 8 to Class 7 sales, coupled with a short-run decrease in Class 7 sales. All else equal, these results are indicative of possible class shifting from Class 7 to Class 8 but importantly, they are not definitive, and do not explicitly demonstrate that class-shifting is occurring.

This study identifies evidence of short-term pre-buy and low-buy in the Class 8 heavy duty freight sector. Pre-buy and low-buy elasticities, coupled with anticipated regulatory costs suggest mixed evidence that the relationship between regulatory cost and HDV purchases is elastic, again with only short-term effects. In both cases low bound estimates were inelastic, indicating little change in purchasing behavior per unit price increase, while upper bound estimates were elastic. We find evidence of cross price (pre-buy) elasticities (where a significant effect is found) between 0.681 and 1.712 and price (low-buy) elasticities of demand between 0.558 and 2.347. These two sets of estimates are in good agreement and are best considered in the context of their time of significance. The magnitude of the effects of regulations depends on both the magnitude of the elasticity and its duration. Pre-buy and low-buy effects, where they occur, are short lived, with the period of significance not extending beyond 8 months pre and post regulation.

These results are beneficial to EPA and regulatory agencies as they may be applied to help determine the magnitude of behavioral changes anticipated due to regulation. The duration of the effects observed are typically short-lived and as therefore duration is an important consideration when applying these results in the context of the magnitudes of the coefficients.

1 Introduction

Heavy duty vehicle (HDV) activity in the United States has increased significantly in recent years, with HDV vehicle miles traveled (VMT) increasing by over 34% between 2000 and 2017, and total fuel consumption increasing 18% over the same period, despite per vehicle fuel consumption falling by 14% and per vehicle annual miles falling by 2.5% (Wards Intelligence 2019; EPA 2019a), EPA, 2019a). Because of this growth in activity, HDVs have become a major source of criteria pollutants throughout the country and are responsible for significant levels of particulate matter (PM) and nitrogen oxides (NOx) in many urban areas. These pollutants are linked to negative health effects including asthma, cancer, cardiopulmonary disease, and premature mortality, and other societal costs such as hospital visits and missed days of school and work (Davidson, Phalen, and Solomon 2005; C. A. Pope 2000; C. Arden Pope 2007; Sydbom et al. 2001). Though far outnumbered by light duty vehicles (LDVs) in 2014 HDVs contributed 35% more PM emissions than LDVs (EPA 2019a).

Over the past few decades, the federal government has made an effort to reduce the negative impacts of HDVs by implementing a series of emissions standards aimed primarily at reducing PM and NOx emissions from new HDVs. Beginning in 1997, the U.S. Environmental Protection Agency (EPA) implemented various regulations that cut emissions of PM and NOx by over 90% (on a per activity unit basis). These regulations have contributed to widespread improvements in human and environmental health (EPA 2011b) and are deemed highly successful by both the regulated and regulatory communities.

However, these standards normally come at a cost. For example, largely seen as the most extensive (and expensive) HDV purchase costs, since new pollution-control equipment may add capital costs to a vehicle. Moreover, new pollution control technology may also increase operation and maintenance (O&M) costs depending on the types of technology employed (EPA 2000; Harrison and LeBel 2008; Calpin and Plaza-Jennings 2012; Dugan et al. 2017; Rittenhouse and Zaragoza-Watkins 2018). New pollution control equipment may also introduce uncertainty among owners and operators and raise questions about vehicle reliability for those unfamiliar with the technology.

These added costs and uncertainty can reduce the intended effectiveness of a particular regulation in at least two important ways. First, to avoid potentially higher capital costs associated with a new regulation, HDV owners may choose to purchase non-compliant, lower cost HDVs prior to the regulatory implementation date. This is called the *pre-buy effect* in the literature (Winebrake et al.

2015b). A consequence of the pre-buy effect is an increase in pre-regulatory (i.e., "dirtier") HDVs on the roads and a dampening of sales of post-regulatory (i.e., "cleaner") HDVs once regulations area implemented. A pre-buy effect can be exhibited by an increase, ceteris paribus, in HDV sales in the time period leading up to the implementation of a new regulation.

Second, HDV owners may *delay* the purchase of a new HDV until a new vehicle or pollution control technology is proven effective, reliable, and cost-effective. This effect is dubbed the *low-buy effect*. When owners delay the purchase of cleaner, *post*-regulatory HDVs, those owners presumably continue to operate and extend the life of their dirtier, *pre*-regulatory vehicles. Low-buy effects may also be due to the impacts of a pre-buy effect, mentioned above. As with the pre-buy effect, a consequence of the low-buy effect is an increase in pre-regulatory vehicles on the roads and a delay in moving cleaner, post-regulatory HDVs into the vehicle fleet. A low-buy effect can be exhibited by an unexpected decrease in HDV sales in the time period shortly following the implementation of a new regulation.

Third, HDV purchasers may choose to purchase vehicles in a different class when faced with increasing regulatory costs. In instances where buyers move up in vehicle class, this has the unintended effect of adding a vehicle with a larger engine to the fleet than might otherwise have been added, which would lead to increased emissions relative to the smaller vehicle. Class shifting has not been widely studied but is likely to coincide with pre-buy and low-buy behaviors.

These potential purchasing behaviors are important to consider, as they could delay the intended efficacy of emissions standards – at least temporarily. The purpose of this work is to determine whether such effects are statistically observable and quantifiable based on an in-depth time-series analysis of HDV markets.

This report presents the results of a literature review and econometric analysis related to HDV sales, focusing on HDVs in Classes 6 – 8, with the objective of identifying and understanding factors contributing to these sales. The report includes research on the impacts of changes in capital and operating costs on HDV sales, pre-buy and low-buy behaviors, class-shifting, and mode-shifting. Findings are presented in three main sections.

The first section presents an overview of the history of HDV emissions regulations in the United States. The second section presents the theory behind purchasing behavior in periods leading up to an anticipated regulation (or what we call "anticipatory behavior consequences"). These impacts include pre-buy and low-buy effects and class shifting, which are based on capital turnover theory, the equilibrium effects of regulation, transitions during the anticipation period, and impacts of anticipation. This section also presents the economic theory behind different anticipatory responses to regulations. The third section presents our empirical analysis of the impacts of anticipated regulation, with subsections presenting evidence of pre-buy and low-buy effects in the HDV sector; evidence of other effects of regulation on the HDV sector; evidence of pre-buy and low-buy effects in response to anticipated regulation or increased costs in other transportation sectors; key factors or drivers which have been identified as potentially contributing to, or affecting, sales of HDVs and purchase decisions (including exogenous variables and purchase decision process variables); and, key factors which have been identified as contributing to mode-shifting.

2 Literature Review and Economic Theory

2.1 HDV Classes in the United States

The heavy-duty truck sector in the United States covers vehicles with a gross vehicle weight rating (GVWR) greater than 8,500 lbs. Heavy-duty vehicles are further subdivided by vehicle weight as shown in Table 1. This analysis will focus on those vehicles defined as Medium Heavy-Duty Vehicles (MHDV) and Heavy Heavy-Duty Vehicles (HHDV), corresponding to Classes 7 and 8, respectively. Additional data on Class 6 vehicles is included in the appendix.

Table 1: Heavy-duty vehicle weight classifications

Class	GVWR (lb)
2b	8,501 – 10,000
3	10,001 – 14,000
4	14,001 – 16,000
5	16,001 – 19,500
6	19,501 – 26,000
7	26,001 – 33,000
8	33,001+

2.2 HDV Regulations in the United States

The first federal HDV emissions standards were adopted in 1974 (Figure 1), limiting carbon monoxide (CO) emissions to 40 grams per brake horsepower hour (g/bhp-hr), and hydrocarbon (HC) and nitrogen oxide (NOx) emissions to 16 g/bhp-hr. These limits were made more stringent in 1979 and 1985 (limiting CO to 15.5, HC to 1.3, and NOx to 10.7 g/bhp-hr by 1985). The State of California (the only state with the right to adopt its own emission standards under the Clean Air Act) began adopting even more stringent HDV emissions standards beginning in 1987, limiting NOx to 6.0 g/bhp-hr and particulate matter (PM) emissions to 0.60 g/bhp-hr.[1] During the 1990s, several HDV emissions standards were adopted which required the development of new emission control technologies to meet the requirements. These included the 1991 federal standard for PM of 0.25 g/bhp-hr, the 1994 PM standard of 0.10 g/bhp-hr, and NOx limitations, which became increasingly stringent, reaching a limit of 4 g/bhp-hr by 1998. Between 1998 and 2003, manufacturers could voluntarily certify engines to meet optional Clean Fuel Fleet standards (EPA 2019b; DieselNet 2020).

In 1997, EPA adopted emissions standards for HDVs model year 2004 and later, which reduced the NOx emissions limit to ~2.0 g/bhp-hr, and which were intended to align with California's standards. To achieve the 2004 standards, most manufacturers used exhaust gas recirculation technology on HDV engines, often with diesel oxidation catalysts. Meeting the 2004 standard was actually required of most manufacturers ahead of the regulatory schedule by consent decree, as early as October 2002[2], and so these standards may also be referred to as the "2002 standards." For consistency this report refers to these standards as the "2004 standards" or "2004 regulations," unless referring to the specific year in which the standards were enforced.

In late 2000, EPA signed emissions standards for HDV highway engines, model year 2007 and later; and in 2001, California adopted nearly identical standards. These standards included stringent limits for PM (0.01 g/bhp-hr, beginning 2007) and NOx (0.20 g/bhp-hr, phased in between 2007 and 2010, and based on a percentage of manufacturer sales). In practice, most manufacturers did not meet the NOx standard until 2010, when all engines were required to comply; because of the

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[2] See, for example, https://www.epa.gov/sites/production/files/2013-09/documents/cumminscd.pdf

difference in engines between 2007-2009 and 2010, some refer to the "2010 standards" as the time in which new NOx standards were implemented (DieselNet 2020; EPA 2019b).

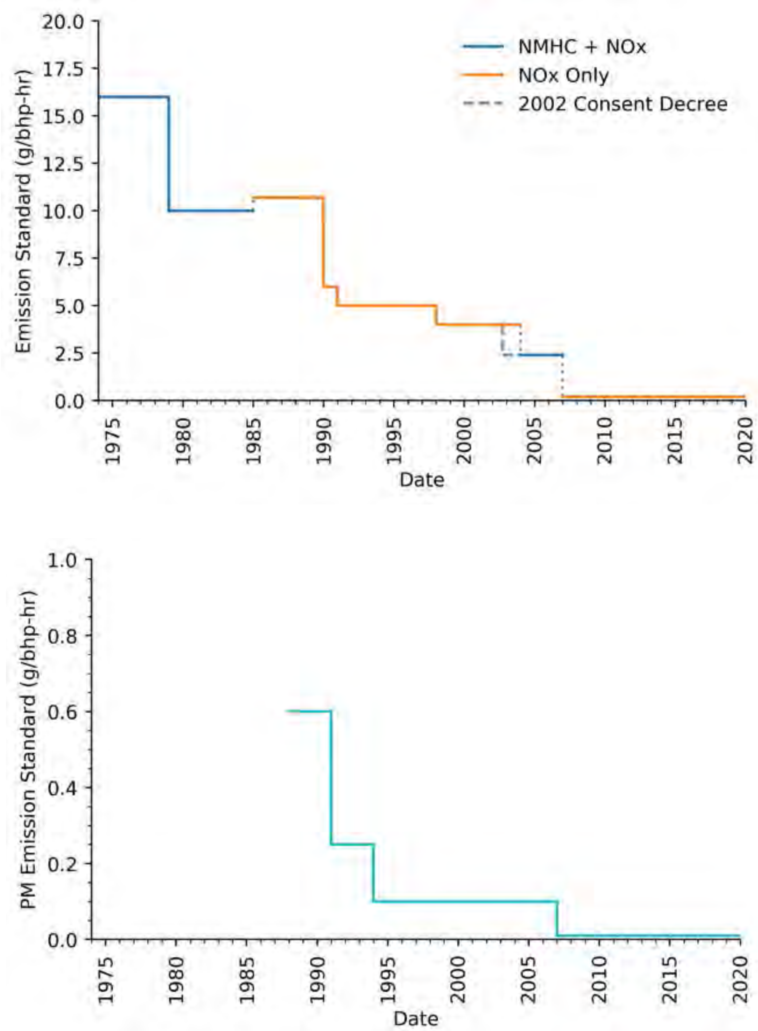

Figure 1: U.S. EPA exhaust emission standards for heavy duty highway compression ignition engines and buses (Top panel: NOx and NMHC + NOx, Bottom panel: PM)

In October 2014, California adopted optional Low NOx standards for HDVs, under which manufactures may choose to certify their engines to three NOx standards: 0.10, 0.05, or 0.02 g/bhp-hr (DieselNet 2020). Also, in 2014, the Federal government implemented new GHG rules for all Class 2b and higher vehicles. Class 7 and 8 combination tractors purchased from 2014 onwards are required to include aerodynamic improvements, subject to the vehicle type, and emission standards phasing in to the 2017 levels shown in Table 2, achieving a 9-23% reduction in CO_2 emissions and fuel consumption compared to 2010 baselines.

Table 2: 2017 EPA/NHTSA Greenhouse Gas Combination Tractor Standards (EPA 2011a)

	EPA Emissions Standard (gCO_2/ton-mile)			NHTSA Fuel Consumption Standard (gal/1,000 ton-mile)		
	Low Roof	Mid Roof	High Roof	Low Roof	Mid Roof	High Roof
Day Cab Class 7	104	115	120	10.2	11.3	11.8
Day Cab Class 8	80	86	89	7.8	8.4	8.7
Sleeper Class 8	66	73	72	6.5	7.2	7.1

2.3 Economic Theory on the Effects of Changes in the Cost of HDVs on Sales

New performance standards that increase the cost of HDVs can result in impacts in the HDV markets (GAO 2004). Economic theory suggests that new standards can influence purchasing decisions, the equilibrium level of HDVs in use, and the age distribution of the HDV fleet. In particular, increases in the cost of new vehicle ownership are expected to lower the demand for new HDVs. Many factors may influence the relationship between HDV demand and cost, including the impacts of firm behavior in the purchase patterns of HDVs when a price increase is anticipated such as pre-buy and low-buy and anticipatory behavior leading to substituting other goods i.e. mode-shifting and class-shifting.

2.3.1 Economic theory on the equilibrium level of HDVs in use

In a market for durable goods such as HDVs, the equilibrium number of HDVs in use is a function of the demand for the services produced by the HDVs (which impacts the demand for HDVs) and the supply of HDVs, both of which are functions of HDV price. Firms make decisions based on the level of service it provides with its fleet of HDVs and the price of HDVs, which we assume is given (i.e., it is a competitive market, so firms are price-takers).[3] A profit-maximizing firm purchasing HDVs makes two entwined decisions with respect to the composition of its HDV fleet:

[3] This discussion uses simplifying assumptions to explain the general theory of the impacts. In reality, large purchasing firms may have stronger price negotiating power than smaller firms, and so may receive beneficial pricing. Conversely, manufacturers may also exert market power as the number of firms is low

the decision about when to retire an HDV and the decision about when to purchase a new HDV. Other operational decisions, including utilization rates, are assumed to be embedded in scrappage and new purchasing decisions. Under equilibrium conditions, the profit-maximizing decision to retire an HDV occurs simultaneously with the profit-maximizing decision to purchase a new HDV (Rittenhouse and Zaragoza-Watkins 2018). Subsequently, firms will adjust their retirement and purchasing decisions until the market reaches the new equilibrium quantity of HDVs for which all firms are at their profit-maximizing equilibrium in retiring HDVs and purchasing new HDVs.

For trucking companies operating in competitive markets, freight rates are set equal to marginal costs, and as such these companies may find it difficult to engage in pre-buy, low-buy, or class switching behavior. Firms operating in less competitive markets, or those where they have some pricing power, have more ability to engage in pre-buy, low-buy, or class switching as they are more able to set the price of freight. Smaller firms, including owner-operators, typically have lower pricing power, and as such are less likely to engage in pre-buy, low-buy, or class shifting behavior. These smaller firms make up a plurality of the companies but operate the minority of vehicles. Data from 2018 show that around 90% of carriers operate 10 or fewer power units (FMCSA 2020).

2.3.2 Capital purchase decisions

The basic economic theory of supply and demand indicates that when the price to produce a good changes, the equilibrium price and quantity sold change. Emission control technologies typically lead to increased costs for compliant plants, which results in reduced demand as the equilibrium shifts to lower quantity at higher prices (see, for example Benishay and Gilbert R . Whitaker 1966; Oum, Waters, and Yong 1992).

An HDV is a capital investment, so purchase and retirement decisions are indicated by capital turnover theory. An HDV contributes positive profit to a firm when the net present value of future revenues exceeds the net present value of costs of the HDV. Firms will use HDVs until they no longer contribute positive profit, which is the point at which revenues from the vehicle equal costs.

2.3.3 HDV retirement decisions

Once a firm purchases an HDV, it will continue to use the HDV while it contributes positive profits; that is, that revenue from the use of the HDV exceeds the cost to operate the HDV. HDV retirement decisions may include scrappage if the vehicle is at the end of its useful life, or resale into the second-hand market for mid-life vehicles, in which case the retirement decision should also take into account the expected resale value of the vehicle. The purchase price of a new HDV impacts a firm's decision to purchase an HDV. Firms will purchase new vehicles when the net present value (NPV), which includes the operating costs as well as the stream of revenue generated by the vehicle, exceeds the purchase price of the vehicle. When regulations are anticipated to change vehicle prices, firms must also adjust their marginal purchasing decisions.

2.3.4 The role of anticipation of the price change

Regulations can lead to higher prices borne by firms in two ways. First, regulations requiring emission control technology may increase the purchase price of a truck. Second, regulatory compliance may lead to higher operating and maintenance costs. With these factors under consideration, firms may choose from a set of decisions, in addition to operating under business as usual conditions, where the regulation may not affect purchasing decisions, i.e. "the "do nothing" scenario. First, they may pre-buy vehicles to avoid higher vehicle costs post-regulation. Second, the may buy fewer higher cost vehicles post-regulation, and third they may purchase vehicles of a difference class.

When a requirement for reduced emissions from HDVs is set at a particular date, firms anticipate that the cost of HDVs is likely to increase at that time along with additional uncertainty. To avoid potentially higher capital costs associated with a new regulation, firms may choose to purchase HDVs prior to the regulatory implementation date. This is called the pre-buy effect in the literature (Winebrake et al. 2015b), and is identified by comparing purchasing behavior in pre-regulation periods to the baseline set of observations. That is, pre-buy effects appear to the extent to which purchasing behavior around regulations differs when compared to normal purchase cycles. A consequence of the pre-buy effect is an increase in pre-regulatory (i.e., "dirtier") HDVs on the roads and a dampening of sales of post-regulatory (i.e., "cleaner") HDVs once regulations area implemented. Firms are expected to buy HDVs prior to the implementation of the new regulation until the revenue per HDV is driven low enough to negate the higher net present value of revenue earned due the higher revenue per HDV as the market moves to a new equilibrium.

Furthermore, firms may delay the purchase of a new vehicle until the pollution control technology is proven effective, reliable, and cost-effective, i.e. the low-buy effect. When firms delay the purchase of cleaner, post-regulatory HDVs, those owners extend the life of their dirtier, pre-regulatory vehicles. Low-buy effects may also be due to the impacts of a pre-buy effect, mentioned above. As with the pre-buy effect, a consequence of the low-buy effect is an increase in pre-regulatory vehicles on the roads and a delay in moving cleaner, post-regulatory HDVs into the vehicle fleet. The higher price of HDVs after the regulation is implemented means that purchasing an HDV will lead to lifetime costs that are higher than if purchased prior to regulation. This effect is in turn further tempered by reduced demand for vehicles not just because of higher prices post-regulation, but also because firms may have already recently purchased new vehicles ahead of the regulations.

Pre-buy and low-buy effects may also be entwined. In some instances, pre-buy may lead to low-buy as vehicles that may normally have been purchased in the post-regulation environment are purchased instead during the pre-regulatory period. Low-buy effects may also occur independently, when purchasing decisions are delayed because of technical concerns over the new technology, limited availability of compliant technology, or other unobserved factors.

2.3.5 The role of substitution

The impact of a price increase in HDVs may be influenced by other transportation methods available. Mode-shifting, using other modes of transportation to ship goods, may occur when the price to purchase or use HDVs increases. The extent to which shipping is shifted to rail, barge, or air transportation depends on the types of items being shipped, the relative transit times and reliability of the different types of transportation, and the distance, origin, and destinations of the shipping services (Kaack et al. 2018).

Another type of shifting that may occur is class-shifting, changing the classes of HDVs used. Because trucking firms may use various classes of HDVs as inputs in their production of trucking services, the ability to substitute among classes of HDVs for inputs could impact the effect of an increase in the price of HDVs, particularly if the regulation only affects certain classes or has a substantially greater impact on certain classes. The price elasticity of demand for a class of HDVs is influenced by substitute goods, particularly other classes of HDVs. For example, if the price of class 8 HDVs increases, trucking firms may substitute some class 7 HDVs if they are now relatively less costly to use in providing trucking services.

In instances where firms move up in vehicle class, this has the unintended effect of adding a vehicle with a larger engine to the fleet than might otherwise have been added, which would lead to increased emissions relative to the smaller vehicle. Class shifting has not been widely studied but is likely to coincide with pre-buy and low-buy behaviors.

2.4 Estimating the Effect of Changes in the Price of HDVs on Sales

The effect of a price change can be estimated by running econometric models on time series data. Regressions of HDV sales or production on explanatory variables, or exogenous factors, that are expected to impact sales provide estimates of the relationships between the explanatory variables and HDV sales. Time series models use the variation in the set of explanatory variables over time to explain the variation over time in the dependent variable, HDV sales.

The most straightforward model is a linear regression, which estimates HDV sales as a linear function of the explanatory variables. However, time series data often contain autocorrelation, meaning that the error term at time t is related to the error term at another time, and the error term is not independent and identically distributed, introducing the potential for spurious results. When autocorrelation exists, running an ordinary least squares regression is not appropriate because the standard errors will be incorrect. Thus, testing for autocorrelation and using the appropriate model if autocorrelation exists is important when running time series models. If after addressing any autocorrelation, tests for other sources of non-stationarity should be conducted and, if found, models to correct these should be used.

2.4.1 Considerations in Model Specifications

This analysis focuses on estimating a reduced-form forecasting-type equation, aiming to identify the exogenous factors affecting both supply and demand. In specifying the explanatory variables included in a time series regression on the sales of HDVs, economic theory indicates that macroeconomic variables expected to influence HDV sales such as a general measure of the economy (such as the value of the Gross Domestic Product (GDP) or the S&P 500 index) and factors influencing the cost to run the vehicles (such as oil prices or fuel prices) should be included. Additionally, if there are good substitutes for the dependent variable, any variables available that measure that substitutability should be considered including in the model. However, a variable accurately measuring this substitutability frequently is not available and even if it is, it may be highly correlated with other explanatory variables.

Time or seasonal trends measure variation in HDVs sales due to time. It may be that sales are generally increasing or decreasing over time, or that sales vary throughout the year due to seasonal influences on the purchase decision.

Finally, it is important to model changes that may disrupt the level of sales or the relationship between HDV sales and the explanatory variables included in the regression. This may include a gradual change, such as the role of GDP as a measure of the overall economy, or a distinct change, such as the implementation of a regulation related to the cost to purchase or own the product of interest. A gradual change may be modeled by including an interaction between the explanatory variable and time, which will allow the estimate of the relationship between HDV sales and the explanatory variable (such as GDP) to vary over time. To model a distinct change such as the implementation of a regulation, fixed effects may be included in the model for the time period(s) expected to be impacted. For example, the model could contain a fixed effect for a specified period before the regulation is implemented to capture any pre-buy effects and another fixed effect for a specified period after the regulation is implemented to capture any low-buy effects when the changes due to the regulation are anticipated.

2.5 Empirical Studies on Anticipation Impacts in the Heavy-Duty Trucking Sector

2.5.1 Literature Examining Pre-buy and Low-buy of HDV Trucks

The peer-reviewed literature examining the effects of regulation on HDV sales, particularly related to pre-buy and low-buy, is relatively sparse. The few studies and reports examining this issue have found widely varying estimates of HDV pre-buy and low-buy, likely due to differences in key factors and economic drivers considered—and in some cases due to methods which might result in biased estimates.

Rittenhouse and Zaragoza-Watkins (2018), the most recent and most comprehensive work in this area, examined the period surrounding implementation of the 2007 HDV criteria pollutant emissions standards to examine the effects of anticipated regulation (and anticipated change in price of vehicles) on HDV sales. The authors examined monthly HDV sales over the 25-year period from 1991 to 2015 and developed a model of HDV sales as a linear function of economic drivers including quarterly gross domestic product (GDP), monthly real oil prices, and month-of-year fixed effects. The authors found evidence of a spike in sales of approximately 31,000 HDV trucks in the months prior to implementation of the 2007 regulation, followed by a near-symmetrical reduction in sales in the months immediately after the regulation went into effect—for an overall near zero net sales impact.

Rittenhouse and Zaragoza-Watkins (2018) also examined the effects of other HDV regulations on HDV sales, finding evidence of a modest pre-buy for the 2004 standards (the second most significant HDV regulation after the 2007 standards, in terms of scale and costs), but finding no such evidence for 1998 or 2010—suggesting that the nature and scale of HDV regulations may influence the likelihood and scale of pre-buy or low-buy behaviors. Rittenhouse and Zaragoza-Watkins (2018) performed no tests for stationarity and do not correct time series data for unit roots present in their data.

Harrison and LeBel (2008), in seeking to evaluate the impacts of the 2007 HDV standards on customer behavior, developed a price elasticity model based on time-series regression. The model included steel and iron prices, increased costs due to regulation, and Class 8 truck sales. To develop estimates of increased costs due to regulation (including unit costs—engine, chassis, retooling, and labor costs—and maintenance costs), Harrison and LeBel surveyed three of four major manufacturers. The authors estimated that a one percent increase in the price of HDVs results in a 1.9 percent reduction in HDV sales. The report estimated a pre-buy of ~104,000 in the years 2005 and 2006, followed by a low-buy of approximately 149,000 in 2007 and 2008 (a ratio of about 2 increased sales for every 3 decreased sales). As noted by Rittenhouse and Zaragoza-Watkins (2018), this industry-funded study did not appear to take into account impacts of changes in GDP and oil or fuel prices in their time-series regression analysis and price elasticity model, which, given the timing of oil price spikes and the Great Recession around the time of regulation implementation, could result in biased estimates. Harrison and LeBel (2008) also used surveys of fleets (ATA and NERA) to learn about intentions and behaviors for pre-buying.

Lam and Bausell (2007) examined the effects of EPA's 2004 HDV emission standards on Class 8 truck production, and used time-series data for the period 1992 through 2003 to develop an econometric model of truck production as a function of GDP, diesel fuel prices, truck retail prices (PPI), and time-of-year fixed effects (to account for seasonal changes in production). The extent of the pre-buy was estimated with the use of a binary variable distinguishing the time period 6 months prior to the implementation of the regulation. The authors estimate that truck production was 20-23% higher than would be expected during this 6-month time period. As noted by Rittenhouse and Zaragoza-Watkins (2018), however, Lam and Bausell do not account for potential reduction in sales (low-buy) during the time period directly following implementation, and so the analysis likely results in biased estimates. Rittenhouse and Zaragoza-Watkins (2018) also raise concerns with Lam and

Bausell's use of steel PPI as a predictor of truck PPI, as: (a) truck PPI is not significantly responsive to steel PPI prices, and (b) oil prices are a predictor of steel prices, violating the exclusion restriction.

2.5.2 Literature Examining Emission Impacts of Pre-Buy and Low-Buy

Rittenhouse and Zaragoza-Watkins (2018) estimated the emissions impacts associated with the shift in HDV sales in response to anticipation of the 2007 HDV regulation, using "back-of-the-envelope" calculations of the difference between emissions of the pre-bought vehicles and the (counterfactual) post-regulation vehicles they replace, over the vehicles' lifetimes. Lifetime emissions were calculated based on emissions rates (g/mile) by the year of manufacture for a vehicle, accounting for expected annual VMT per vehicle for a given year in its lifetime, and assuming 10-year vehicle lifetime (estimates for emissions rates and vehicle annual VMT were derived from the California Air Resources Board's (CARB) Emission Factors (EMFAC) database). The authors also accounted for the number of vehicles placed into early retirement due to anticipation (pre-buy), assuming zero (0) at the lower bound and 31,164 at the upper bound. Rittenhouse and Zaragoza-Watkins (2018) estimate the increase in emissions due to anticipation of regulation at over 178,000 tons for NO_x, 10.2 tons for PM_{10}, and 9.8 tons for $PM_{2.5}$ over the remaining expected lifetime of the vehicles studied at the time of the 2007 regulations. Reduced emissions due to early retirement of older, higher-emitting vehicles is estimated to decrease NO_x emissions by 22,000 tons, PM_{10} by 0.6 tons, and $PM_{2.5}$ by 0.6 tons, for a net increase of about 156,000 tons of NO_x, 9.6 tons of PM_{10} and 9.2 tons of $PM_{2.5}$. The social costs of the net increase in these emissions due to pre-buy in anticipation of regulation were estimated at $108.5 to $117.9 million.

Noting the caveats surrounding the approach and findings of their analysis, Harrison and LeBel (2008) used a NERA scrappage and fleet population model combined with the EPA MOBILE6 model to estimate the effects of pre-buy and low-buy on annual HDV emissions, assuming that total HDV vehicle miles traveled remained constant after the standard took effect. With their estimate of 104,077 pre-buy vehicles (in the years 2005 and 2006 combined), and low-buy of 149,272 (in the years 2007 and 2008 combined), the authors estimated that the pre-buy and low-buy behaviors in response to the standard would result in reduced emissions benefits (i.e. emissions higher than expected in absence of pre-buy and low-buy) of roughly 50,000-75,000 tons of NOx annually in the years 2008 through 2010 (Harrison and LeBel, 2008).

2.5.3 Literature Examining Other Effects of Regulation on HDV Sector

Though not specifically examining pre-buy or low-buy behavior related to HDV sales, recent research and commentary have pointed to other impacts of HDV emissions regulations, which may be of relevance to better understanding these pre-buy or low-buy behaviors, or which may shed light on other potentially important effects of these regulations.

In comments to NHTSA and EPA, Calpin and Plaza-Jennings (2012) sought to demonstrate that the EPA underestimated costs of the 2007 HDV emission standards by a factor of 2 to 5, and to explore how and why this happened. Calpin and Plaza-Jennings presented data illustrating trends in HDV sales and average age of HDVs over the time period 2000 to 2010, attempting to illustrate that the regulation led to an increase in sales prior to the regulation, followed by a drop in sales. The graphs, however, do not account for changes in GDP or oil prices—significant factors affecting demand for HDV trucks and purchasing patterns [as noted previously in Rittenhouse and Zaragoza-Watkins, (2018)]—nor do they account for other factors which may influence truck sales or average truck age over time. Calpin and Plaza-Jennings note a trend towards increased use of glider kits (which involve marrying new truck frames and bodies to rebuilt powertrain and suspension) and note that this is one way to avoid compliance with standards. Compliance cost per truck was estimated using "individual sales invoices and OEM sales documents covering truck sales involving the majority of heavy-duty truck and engine OEMs." The authors note that the sample used does not represent all data points, but rather data "readily available" from OEMs; as such, an objective, unbiased sample cannot be guaranteed.

Dugan et al (2017) empirically examined the effects of EPA emissions standards on the financial performance of the trucking industry, using operating ratio (the ratio of operating expenses to operating revenues) as the measure of financial performance. The methodology involved extracting data from 10-K reports for publicly listed trucking companies for the years 1999 to 2009, and weekly national diesel fuel price data from EIA. Panel methods were used to account for environmental, accounting, and industry-specific variables, with companies not in existence in 2002 (the first year of EPA standard implementation) excluded from the analysis. A fixed-effects model was used to estimate changes in operating costs after accounting for all other independent variables. The study identified five main "environmental concerns" noted on 10-K forms, including: increased maintenance costs related to the use of compliant engines; higher fuel costs due to compliant engines' lower fuel efficiency; lower resale value for older trucks; and higher costs of trucks with compliant engines. Firms found to express these environmental concerns were coded as such. The study examined impacts on truckload (TL) and less-than-truckload (LTL) firms separately.

Results suggest that lower fuel efficiency due to use of compliant engines actually decreased the operating ratio of LTL firms (by 3.19%)—meaning that these firms had a lower ratio of expenses to revenue. This is a counterintuitive finding, as one would expect declining fuel economy to result in an increased operating ratio; however, as one company explained in its 2008 financial statements, the company earns higher fuel surcharges in times of increasing fuel prices—which seems to have more than offset the decrease in fuel efficiency. Results suggest that increased maintenance costs and declining fuel efficiency in compliant engines led to decreased operating ratios in the years 2002 to 2006 but led to increased operating ratios in the years 2007-2009 (for both TL and LTL firms). Though capital expenditures are found to be statistically significant, they were found to have little impact on operating ratios for trucking firms. While trucking firms are able to pass some of the increased costs to customers, firms (LTL in particular) are experiencing lower returns on assets (ROA) in response to higher truck prices. Findings suggest that trucking companies may pass capital costs and in some cases fuel costs onto customers and may recoup (or more than recoup) costs. Dugan et al.'s findings (i.e. HDV regulations may result in lower operating ratios) suggest that some assumptions about financial impacts of HDV standards on trucking companies—and thus assumptions regarding trucking firms purchasing behavior—may not apply in certain respects.

It is useful to note that the way that diesel fuel prices, fuel efficiency, and fuel surcharges were handled here may have led to misleading results, suggesting that declining fuel efficiency could lead to improved operating ratios, when in fact the improved operating ratios might result from increased diesel fuel prices and fuel surcharges also occurring during this time.

2.5.4 Literature Examining Vehicle Choice and Class Switching

The incremental costs of regulations can vary by HDV class/size, which may provide an economic incentive for HDV purchasers to switch to smaller (or larger) vehicle classes, referred to as class shifting, depending on the cost differential and the total operating costs of vehicles.

Extensive academic literature covering class-shifting was not identified in this review, after a systematic literature search. This was also the case in 81 FR 73478 (Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles-Phase 2 pp. 73873-73874): "The agencies, along with the NAS panel, found that there is little or no literature which evaluates class shifting between trucks." In general, the sparse literature on this subject indicates that the scale of class switching in response to HDV emissions regulations would be minimal, as various barriers to class switching exist.

One study estimated the impacts of HDV class-switching, specifically a shift from larger trucks to smaller trucks, in response to proposed HDV restrictions, and found that total VMT and fuel consumption would increase, as would net emissions of some pollutants (i.e. carbon monoxide). Other pollutants (namely NO_x) would decrease in many cases (Campbell 1995). At the time of Campbell's analysis, many firms (carriers and distributors, etc.) indicated an intent to switch to smaller trucks. The HDV class-shifting explored in Campbell (1995) is of tangential relevance to this work (and to HDV emissions standards), however, as the anticipated class shifting was in response to proposed (mid-nineties) regulations that would prohibit large trucks from operating in certain areas (e.g. Los Angeles) during typical daytime hours, to reduce congestion and emissions. Large truck bans would effectively cease activity of many firms during the day and would not allow for certain time-critical deliveries, so the economic incentive to switch to smaller trucks was much more significant than is the case with emissions standards.

The vehicle choice literature examines which vehicle, or set of vehicles, a firm would choose for a given shipment or regular activity, and what are the main determinants of these choices. There are a number of variables that significantly influence freight vehicle (and mode) choice, including: shipment size, distance, frequency, commodity characteristics, vehicle age, vehicle fixed costs and operating costs, firm characteristics such as fleet size, agents involved (shippers, carriers and receivers) and their preferences (e.g. rates, transit time and reliability), and economic activity at shipment origin and destination (Abate and De Jong 2014; Holguín-Veras 2002; Holguín-Veras et al. 2021).

Abate and De Jong (2014), found that the main determinants of vehicle size choice are shipment size and distance, vehicle operating cost, vehicle age and carrier type (e.g. fleet size). Specific to cost, higher variable operating costs (i.e. fuel prices) increased the probability of larger vehicles being selected, while higher total fixed costs led to a gradual shift towards smaller vehicles being selected. If these results from Denmark apply to trucking firms in the United States, the net impact of HDV emissions standards on vehicle size, then, would be dependent on the nature of regulations, and the cost components involved. Abate and De Jong (2014) examined how firms allocate trucks across hauls, and so the findings may be of more relevance to vehicle choice among existing vehicles owned or used by the firm, as opposed to replacing existing vehicles.

A recent study exploring the impacts of an emissions-based truck charge in the Netherlands (de Bok et al. 2020) found that, though the charge would lead to lower-emitting vehicles, it would not result in a significant increase in shipment sizes or shifts to other vehicle types. The authors note the importance and impact of warehousing costs on firms' decisions related to vehicle choice and shipment size, and how failing to take into account the impact of warehousing costs in analyses can overestimate the potential shift between vehicle sizes. Additional explanations for the minimal scale of estimated shift between vehicle sizes are the relative costs presented by vehicle charges compared to total transport costs (e.g. warehousing but also fuel costs and other operational costs), and the existing structure and logistical environment of transport, where only one vehicle type may be possible, or only one vehicle choice is available to a firm (i.e. containerized transport and tractor-trailers).

Most recently, Holguín-Veras et. al (2021) conducted a nationwide qualitative and quantitative effort to understand factors behind freight mode choice. In addition to identifying a number of complex and interrelated factors behind freight mode and vehicle choice, the authors identified that freight mode decisions are made based on interactions among shippers, carriers and receivers. Absent a solution that benefits all parties, the agents with the most power have the most influence over decisions about how to deliver shipments, and when. As carriers' positions have weakened after deregulation and subsequent over-supply, shippers and receivers have held relatively more power, and are able to decide on shipment size and frequencies that minimize their total costs (transportation plus inventory). This is of potential relevance in the context of HDV emission standards as it suggests that carriers have less power to make independent and isolated decisions in response to HDV emissions standards, and are instead (at least partially, and apparently increasingly) responding to the wants and needs of shippers and receivers.

2.5.5 Literature Examining Pre-buy/Low-buy in Other Transportation Sectors

Recent research and data have indicated that pre-buy and/or low-buy behaviors have taken place in other transportation sectors—specifically in Denmark, in reference to an announced tax hike on electric vehicles, and in the maritime shipping sector, in response to the IMO Tier III standards. These studies provide evidence of pre-buy/low buy in other sectors and regions, where regulations (or policies which will increase costs for the purchaser) were announced well ahead of implementation, and where regulation would increase costs to the purchaser/owner.

Asplund et al. (2019) examine pre-buy behavior in response to a tax hike on electric vehicles in Denmark, which was announced in 2015, several months prior to its implementation. Asplund et al. use monthly vehicle registration data (for key subsets of the vehicle population, e.g. premium vehicles and Tesla Model S) during the period 2013 to 2017, adjusting for seasonality, and find that the announced tax hike led to a surge in registrations of Tesla S vehicles in the period leading up to the tax hike, followed by a dramatic drop in registrations in 2016, after the tax hike was instated. In late 2015, 1887 Teslas were sold, compared to the authors' predicted 312 sales for the time period (had no change in taxes occurred). In contrast, only 78 Teslas were sold in the entire 2016 calendar year, compared to a predicted 1684 sales. Asplund et al. also compare sales trends in Denmark to sales trends in Europe and the U.S. (establishing a counterfactual of sorts), demonstrating that a similar sales pattern did not take place elsewhere.

A report by Starcrest Consulting Group, LLC. (Starcrest 2017) recognizes the potential impacts of the International Maritime Organization (IMO) Tier III standards for nitrogen oxides (NOx) emissions from diesel engines. The Tier III standards are structured around a ship's keel laid date, with the most stringent standards applying to ships with a keel laid date on or after January 2016. The laying of a ship's keel typically denoted the official beginning of a ship's construction, but a keel can be laid far earlier than the commencement of the actual construction. The consequence of this regulation structure, the report indicates, is that many (1,430) ship keels have been laid in the period 2005 to 2015, for which construction has not yet begun, and for which Tier III standards will not apply once the vessel is actually constructed and operational. The impact is particularly apparent in the year 2015, when fully 1,211 keels were laid, but waiting for construction; in 2016, this number dropped to 99.

2.6 Literature Examining Factors Influencing HDV Sales or Trucking Activity

To estimate the impacts of HDV regulations on HDV sales, an understanding of the key factors driving and influencing HDV sales is necessary. Several studies and reports have explored key factors driving and influencing HDV sales—although in many cases indirectly—or have explored factors influencing demand for trucking freight activity. As described in greater detail below, factors found to influence HDV sales and/or truck freight activity include economic activity, oil and diesel fuel prices, time of year or seasonality of purchase cycles, HDV or truck prices, and truck freight activity (for HDV/truck sales). In several cases, there is disagreement in the literature regarding the significance of, or regarding the appropriateness of including, these factors in seeking to estimate or predict HDV sales; these varying perspectives are presented in the following subsections.

2.6.1 GDP and other measures of Economic Activity

Rittenhouse and Zaragoza-Watkins (2018), using quarterly gross GDP (Gross Domestic Product) data from the Bureau of Economic Analysis and Monthly Class-8 HDV sales for the U.S., from Ward's Automotive, Inc., found GDP to be a significant predictor of HDV sales for the period 1991 to 2015; Lam and Bausell (2007) found truck production for the period 1992 to 2003 to be a function of GDP as well. Gately (1990) and EPA and NHTSA (EPA 2011a) found GDP to be a predictor of trucking activity (vehicle miles traveled—VMT), while others (e.g. International Energy Agency (IEA 2017) and OECD (2004), among others) have noted the connection between GDP and trucking activity.

The relationship between GDP and HDV sales or trucking activity may be more complex than studies have suggested and may be changing over time. International Energy Agency (2017) and OECD (2004), for instance, suggest that a decoupling between GDP/economic activity and trucking sector or freight transport activity might be taking place (or has taken place) in the United States, as the U.S. has seen a shift from goods production to services.

OECD (2004) also recognizes the changing structure of the economy, and how certain economic sectors are more associated with freight transport, as opposed to the economy in general. The report makes use of Transportation Satellite Accounts (TSA), which measure transport expenditures in different sectors of the national accounts and can provide more detailed estimates of transportation services demanded by certain industries and sectors (transport intensity of sectors). The report finds a higher share of high-value, low-transport-intensive sectors in U.S. GDP (such as services and certain manufacturing), compared to the share of transport-intensive, lower-value industries and sectors such as agriculture or basic chemicals. The report also notes the increasing share of high-value-added industries in the U.S. freight movements. OECD (2004) findings suggest that the changing relationship between GDP and trucking freight activity over time may be important to consider; as opposed to simply exploring the relationship between GDP in general and trucking activity and sales, the relationship between freight trucking activity (and HDV sales) and specific sectors of the economy, too, may be important to consider, as it may reveal stronger associations between certain sectors and trucking activity, and potentially HDV sales.

Alternative measures of economic activity might be important to consider as well. The National Academies' (National Academies of Sciences Engineering and Medicine 2012) and Winebrake et al. (2015) note that international trade may be a better determinant of trucking activity (VMT) demand than GDP, hypothesizing that while GDP measures both goods and services, international trade measures movements of goods, which is a better proxy for trucking activity. Winebrake et al (2015) remove petroleum from the international trade variable, to remove possible interdependence between these variables.

Rittenhouse and Zaragoza-Watkins (2018) examine lagged and lead GDP in multiple time increments (number of months), in addition to their preferred specification using quarterly GDP. Winebrake et. al (2015) also use lagged dependent variables in analyzing determinants of demand of combination trucking activity and note the potential importance of lags in capturing these relationships, given the structure of the industry (i.e. longer-term contracts, fixed infrastructure, and/or long-term service agreements).

Rittenhouse and Zaragoza-Watkins (2018), in alternative model specifications of their analysis (described above), examined effects of alternative macroeconomic variables, including: S&P 500 index; U.S. Treasury securities yield curve, six-month London Interbank Offer Rate (LIBOR), 3-month lead of GDP, and 3-month, 6-month and 12-month oil futures contracts traded on the New York Mercantile. Rittenhouse and Zaragoza-Watkins found that when considering these variables, the policy coefficients remained stable (that is, these variables did not measurably change key coefficients or the goodness of fit), suggesting that additional macroeconomic variables could be excluded from the analysis.

The range of findings related to economic activity measures and their respective relationships to HDV sales and trucking sector activity—and the indication that these relationships may be changing over time as the U.S. economy shifts to service-driven growth—suggests that further exploration of the relationship between economic activity and HDV sales and/or trucking activity are warranted, as is further exploration of appropriate measures of economic activity (e.g. GDP, activity in certain sectors, international trade) as influencing trucking activity or HDV sales.

2.6.2 Oil Prices and Diesel Fuel Prices

Rittenhouse and Zaragoza-Watkins (2018) found oil prices to be a significant predictor of HDV sales for the time period 1991 to 2015, while Lam and Bausell (2007) found HDV sales to be a function of diesel fuel prices, for the period of 1992 to 2003. Rittenhouse and Zaragoza-Watkins

(2018), however, in examining the relationship of fuel prices to Monthly Class-8 HDV sales for the U.S. (from Ward's Automotive, Inc.), found monthly real oil prices from the Energy Information Administration (EIA) to be a stronger predictor of HDV sales, compared to diesel fuel prices—particularly in the presence of month-of-year fixed effects.

The relationship between fuel prices and HDV sales may be more complex than analyses have indicated, however, or may be changing over time. Rittenhouse and Zaragoza-Watkins (2018) analyzed the influence of oil prices on HDV sales over time, with results suggesting a structural shift in the relationship after 2001 (oil prices are a positive, significant driver of sales before 2001, and a negative, insignificant driver after 2001). These findings echo those of Winebrake et al. (2015b), who found a shift in the relationship between fuel prices and trucking activity, albeit for a different timeframe—finding combination truck activity (VMT) to be elastic to diesel fuel prices in a regulated environment (1970 to 1979), but inelastic to diesel prices in a deregulated environment (1980 to 2012). Winebrake et al. (2015a) found single unit truck activity to be inelastic to diesel fuel prices.

The disparity of findings related to oil and diesel fuel prices and their relationships to HDV sales and trucking sector activity, and the indication that these relationships have changed (or continue to change) over time, suggest that further exploration of the relationship between petroleum prices and HDV sales and activity are warranted.

2.6.3 Time of Year, Seasonality, Purchasing Cycles, and Backlogs

Rittenhouse and Zaragoza-Watkins (2018) and Lam and Bausell (2007) find time of year to be a significant predictor of HDV market activity, with Rittenhouse and Zaragoza-Watkins (2018) accounting for month-of-year fixed effects in predicting HDV sales, and Lam and Bausell (2007) accounting for quarterly, or seasonal, changes in HDV production.

Rittenhouse and Zaragoza-Watkins (2018) note that HDVs do not follow model-year production cycles, but instead are produced in response to orders received by purchasers; there is typically a several-month lag between order and delivery. Other sources (e.g. Phillips (2018)). have noted that typically the backlog for HDVs (from order to delivery) is about 5 months but has reached 9 months in times of high demand (for instance in 2018, the largest backlog since 2006).

Communication with industry professionals (Pers. Comms. Anthony Greszler) support and shed additional light on the structure and process of vehicle ordering and pricing, noting that class 8 trucks are generally built to order based on buyer specifications, and there is typically a period of around 2 months between date of order and date of delivery. While 2 months is the typical lag period, during periods of high demand this wait time may be as much as six or more months. Conversely, during periods of low demand, delivery times may be on the order of 1-2 months.

As orders are typically customized pricing is generally quoted at time of order based on specified characteristics, with discounts available for buyers based on volume of purchases or pre-existing relationships. As such, the concept of a "sticker price," similar to that seen in the passenger vehicle market, does not apply as directly to the heavy-duty sector, with prices varying based on buyer preferences, rather than specified manufacturer models. Furthermore, buyers may cancel orders with minimal penalty should economic conditions change, or other factors affect purchasing decisions. For example, many buyers express concerns over how new vehicles will function with new technologies and may wish to wait until the technologies become more tested and proven across the industry. As a result, sales data generally reflect date of delivery, not date of order, and thus anticipatory behaviors around vehicle purchases likely occur months ahead of observed delivery dates.

These patterns point to the importance of understanding timing of HDV sales, as well as the definition of a "sale" (i.e. whether a sale indicates an order or a delivery), and to consider lags/backlogs to the extent possible when seeking to understand trends in HDV sales.

2.6.4 Truck/HDV Prices or Price Index

Lam and Bausell (2007) examined the effects of EPA's 2004 HDV emission standards on Class 8 truck production and used time-series data for the period 1992 through 2003 to develop an econometric model of truck production as a function of GDP, diesel fuel prices, truck retail prices (PPI), and time-of-year fixed effects (to account for seasonal changes in production). In their basic model, Lam and Bausell (2007) found truck price to be a highly significant predictor of HDV production, however, once other relevant and significant factors were taken into consideration (e.g. inclusion of lagged variables and accounting for autocorrelation), HDV truck price (PPI) was not found to be a significant predictor of HDV production. Lam and Bausell (2007) incorporate steel prices into a version of their model, in which they attempt to correct for endogeneity of HDV PPI and HDV production. Rittenhouse and Zaragoza-Watkins (2018), however, raise concerns with the use of steel PPI as a predictor of truck PPI, as noted previously, as: (a) truck PPI is not significantly responsive to steel PPI prices, and (b) oil prices are a predictor of steel prices, violating the exclusion restriction.

Harrison and LeBel incorporated a price elasticity model, based on time-series regression, into their analysis of impacts of 2007 HDV regulation, and estimated a -1.9 elasticity—meaning a one percent increase in HDV truck price would decrease demand for HDV trucks by 1.9%. As Rittenhouse and Zaragoza-Watkins (2018) note, however, Harrison and LeBel failed to account for GDP and oil prices, two significant drivers of HDV demand that they identify, which were also changing during the time period of the analysis.

Askin et al (2015) describe an HDV consumer (purchaser) choice and HDV stock model, and investigate factors leading to adoption of certain HDV technologies (efficient and alternative fuel technologies, in particular) with the purpose of forecasting adoption of HDVs by fuel and technology type, and garnering insights into factors inhibiting and driving this adoption. In their HDV consumer choice and HDV stock model, they assume that vehicle cost is an important factor in vehicle purchase decisions when comparing vehicles and assume -6 price elasticity (a 1% increase in price is assumed to result in a 6% decline in demand) at 50% market share. The authors, however, recognize the substantial uncertainty in their price elasticity estimate (for which, they note, estimates for purchasing vehicle X versus vehicle Y in the light duty vehicle (LDV) market range from -1 to -8) the authors account for this uncertainty in their sensitivity analyses. Additional variables and inputs include generalized cost of vehicles, including fuel costs, assumptions on acceptable payback period based on fleet size, penalties for alternative fuel vehicles to quantify concerns with refueling time, and a factor to account for fueling infrastructure availability.

Miller, Wang, and Fulton (2017), a UC Davis project report, involved the development of a decision choice model for truck vehicle and fuel purchasing in California and an analysis of market penetration scenarios, primarily in the context of California's transition to ZEVs. In contrast to many models examining market penetration scenarios, this report uses a fleet decision choice model informed from actual discussions with stakeholders in trucking fleets. The value of the many factors was estimated through a series of interviews, surveys, a truck choice workshop, expert judgement, and self-described "basic logic." A nested multinomial logit model was developed, which monetizes many of the factors to estimate generalized cost, and which models truck decision purchase behaviors. Truck capital cost was a key input to the decision choice model, as were other costs including fuel cost (which here is the present value of fuel price and fuel economy of the vehicle over lifetime); maintenance costs; incentives; carbon tax. Non-monetary variables such as green public relations, refueling inconvenience, and availability cost (perceived difficulty in purchasing a vehicle due to limited availability) were also included in the model.

Rittenhouse and Zaragoza-Watkins (2018), the most recent and comprehensive study of the effects of anticipated regulation on HDV sales, did not incorporate HDV price into their model, recognizing that the pollution-control equipment required by the 2007 HDV regulation increased the cost of HDVs, and so if costs were passed onto HDV purchasers, or if price was endogenous to demand, including price in the regression would absorb some of effect of the regulation on HDV sales, but would not account for other effects including reliability. The authors also note that if the regulation induced HDV producers to increase the price of HDVs themselves (prior to the regulation going into effect), in anticipation of a spike in sales, then excluding price would attenuate their estimates of the effects of regulation on HDV sales. Finally, Rittenhouse and Zaragoza-Watkins (2018) note that seasonal fluctuations in HDV prices in response to demand cycles (year or month-of-year) should be absorbed by fixed effects.

The disparity of findings related to HDV price and its significance in influencing HDV sales suggests that further exploration of the relationship between HDV prices and HDV sales is warranted.

2.6.5 Truck Freight Activity/Demand

In the HDV consumer choice and HDV stock model developed by Askin et al. (2015) (described above), HDV truck stock growth is assumed to scale with growth in truck freight demand, which is estimated from the U.S. Department of Transportation (DOT) Federal Highway Administration's Freight Analysis Framework (FAF) model; the growth rate in HDV stock is assumed to match the percentage growth in freight ton-miles (ton-miles are assumed to be exogenous, and rebound effect in response to efficiency improvements is not considered).

Harrison and LeBel, as part of their model estimating the effects of 2007 HDV regulations on HDV sales, assume that HDV sales are partially a function of HDV VMT, as estimated by EPA's MOBILE model.

Government agency models and reports (e.g. FHWA Freight Analysis Framework, EPA MOBILE and MOVES) often assume that HDV sales and stock are a function of HDV trucking activity, as have analyses such as Harrison and LeBel. This suggests that the relationship between trucking activity and HDV sales may warrant further examination, as trucking activity (current year, previous year, or later year) may function as a predictor of HDV sales, at a level equal to or superior to that of the variables typically used (i.e. those described above—economic activity, fuel prices, seasonality, or HDV prices).

2.7 Literature Examining Mode Choice

The literature exploring mode choice is extensive, and a comprehensive review is beyond the scope of this work, which largely focuses on responses to anticipated regulation, and factors influencing HDV sales. In general, mode shifting between trucks and rail or barge in response to changes in costs of trucking is not widely expected due to a number of factors, including shipment-specific factors, with certain commodities and shipment distances less likely (or unable to be) substitutable; and the availability, or lack thereof, of alternative modes for shipments, and related infrastructural or capacity constraints (Winebrake et al. 2012). The shorter the shipment distance the more likely it is that only one mode (i.e. truck) is available, and most truck shipments in the United States are relatively short (100-500 mile) distances (Winebrake 2009; Winebrake et al. 2012) . Rail shipments tend to travel longer distances, and be more sensitive to fuel costs, while truck shipments are more expensive per unit cargo and more time sensitive. Research has indicated that even a 50% increase in trucking fuel price, and the corresponding increase in operating costs, does not cause a significant mode shift from truck to rail (Winebrake et al. 2015b, 2012; Oum, Waters, and Yong 1992; Samimi, Kawamura, and Mohammadian 2011).

This literature review focuses on responses to anticipated regulation, and factors influencing sales of HDVs, and HDV freight activity in general. As such we include summaries of two recent works on the subject of mode shifting, which may provide insights into understanding, and capturing underlying factors behind, trends in truck freight and truck sales over time—one through a review of factors influencing mode choice, and one through examining the impacts of fuel prices and truck fuel economy on mode choice.

Kaack et al. (2018) describe factors associated with mode choice in a decarbonization context, and review and explore approaches which could be used to encourage modal shifts from truck to rail and barge. Factors associated with mode choice include quality of service, shipment and commodity characteristics, transit time and reliability, shipment costs, and environmental considerations (which is noted as a relatively new, and relatively small, concern, though increasing). Kaack et al. (2018)

suggest that modal shifts have the potential to lead to decarbonization and reduce overall emissions, but require incentivization through policy interventions in order lead to widespread changes in mode choice. Policy options or investments to encourage modal shifts include: investment in infrastructure in rail and waterways; intermodal operations research and planning; integration of services between modes; enabling intermodal activity through information technology; regulation and subsidies of low-carbon modes (rail, port and waterway); greenhouse gas (GHG) pricing and internalizing externalities; motor fuel taxes; road user charges; labor rules (e.g. maximum hours of service and minimum wage); and, truck size and weight regulations. Without these interventions, Kaack et al. (2018) suggest that the status quo mode mix is likely to continue.

Bushnell and Hughes (2019) use U.S. Commodity Flow Survey Public Use Microdata (CFS PUM) to estimate mode-shifting in response to fuel price changes and truck fuel economy changes across 34 broad commodity groups[4] and varying shipment sizes. The previously unreleased CFS PUM data include shipment characteristics such as type of good, shipment value, distance, weight, shipment origin and destination (at state or regional level), and shipment mode (including rail, barge, truck, air, multi-modal). In estimating the effects of a fuel price change, Bushnell and Hughes use cross-sectional data (for the year 2012, the most recent year for which CFS PUM data were available) and a multinomial-logit model to estimate the effects of fuel price changes on mode shifting. Fuel prices are based on EIA average diesel prices in the quarter of the shipment, which they acknowledge is a weak explanatory variable as quarterly variation in fuel price was low in 2012. Bushnell and Hughes (2019) find that higher diesel prices may increase probability of mode shifting from truck to rail. Also, improved fuel economy of trucks may induce minor mode shifting from rail to truck, and from air to truck, as the relative costs of trucking are decreased, though results vary widely by commodity. For example, in some cases high value-to-weight ratio commodities such as animals and precision instruments switched from air to truck as truck fuel efficiency improved. Other lower

[4] The authors observed 34 different commodity groups aggregated at the SCTG 2-digit level. These include Agricultural Products, Alcohol, Animal Feed, Animals , Articles of Base Metal, Basic Chemicals, Coal, Fertilizers , Grain, Gravel, Logs and Other Wood in the Rough, Machinery, Metallic Ores, Milled Grain, Miscellaneous Manufactured Products, Mixed Freight, Non-Metallic Mineral Products, Other Chemical Products, Other Coal and Petroleum, Other Prepared Foodstuffs, Paper, Pharmaceuticals, Plastics and Rubber, Precision Instruments, Primary Base Metal, Printed Products, Pulp, Newsprint, Paper, and Paperboard, Sand, Textiles, Transportation Equipment (not elsewhere classified), Vehicles, Waste and Scrap, and Wood Products

value commodities, such as paper products and fertilizers, did not see similar effects. The approach did not seem to take into account (or differentiate) the effects of fuel surcharges, which are associated with fuel price increases, but are not always associated with fuel economy. The actual fuel economy of vehicles is not necessarily taken into account with fuel surcharges, so fuel cost savings due to fuel economy improvements may not be passed onto the customer.

Academic literature covering class-shifting was not identified in this review after systematic literature search. This was also the case in 81 FR 73478 (Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles-Phase 2 pp. 73873-73874): "The agencies, along with the NAS panel, found that there is little or no literature which evaluates class shifting between trucks."

2.8 Anticipated and Observed Costs of Heavy-Duty Truck Regulations

Potential purchasers of HDVs are expected to respond to anticipated costs of regulations in making pre-buy purchase decisions. In attempting to understand and quantify pre-buy effects of EPA HDV regulations, therefore, the *anticipated* or *estimated costs* of these regulations are important to consider—as opposed to the *actual* costs of past regulations. Some sources indicate that actual or effective costs of U.S. HDV emissions regulations are significantly lower than those estimated prior to implementation of the regulation (e.g. Posada et al. (2016)), while others suggest the actual costs were much higher than costs estimated prior to implementation (e.g. Calpin and Plaza-Jennings, 2012). If actual costs differ considerably from anticipated or estimated costs, the use of actual costs in analyses may result in biased estimates of expected responses by HDV purchasers to future anticipated changes in HDV costs.

Emissions standards may increase the cost of HDVs in a number of respects (EPA 1997, EPA 2000, Krishnan and Tarabulski, 2005, Posada et al. 2016). The first is the upfront capital cost, which may be increased in response to requirements for hardware, equipment and other technologies to meet the standards (for instance, emissions control aftertreatment or improved engine systems or modifications). Inclusion of these technologies involve costs to the manufacturer, such as components, labor and potentially research; manufacturer costs are then passed on to the HDV purchaser. Emissions standards may also increase the operating costs of HDVs, by requiring increased maintenance and/or repairs of equipment, or by increasing fuel costs due to reduced fuel efficiency and/or increased fuel prices, if cleaner fuel is a requirement of the standard. Specific costs vary by regulation, vehicle class, size, and fuel type (diesel or gasoline), and even by time within a regulation period—as the costs of new emission control technology may decline over time with scale, and as manufacturers move along the learning curve.

Table 3 presents a range of estimated costs of HDV truck emissions regulations, as reported in U.S. EPA Regulatory Impact Analyses (RIA) and similar documents; this table is not exhaustive but includes examples of cost estimates which have been identified in this review. These results are simplified for the regulatory periods in this analysis in Table 4. These costs are presented by regulation and year, in nominal and real dollars (2019$)[5]. Table 3 also includes a description of the estimated costs for each regulation and cost component. Reported estimated costs are not consistent in format or content across regulations, as the extent and type of costs calculated has varied over time, partially in response to advances in calculation methods. Estimated increases in costs associated with HDV emissions regulations are derived from engineering estimates and include not only capital costs, but in some cases increases in maintenance and operations costs, including fuel economy penalties associated with certain emissions equipment. Potential purchasers may respond differently to increases in ongoing operations and maintenance costs as opposed to increases in upfront capital costs. Costs also vary by vehicle fuel type (i.e. diesel or gasoline).

The estimated incremental costs of an HDV purchased in the first year of a regulation may be considerably higher than those of a vehicle purchased later on in the regulation cycle (e.g. estimated incremental costs of an HDV purchased in 2004 vs. 2009, or purchased in 2007 vs. 2012, as shown as shown by the difference in near-term and long-term costs.

From the perspective of potential purchasers of HDVs, there are also uncertainty, unfamiliarity and/or reliability "costs" associated with new technologies (Calpin and Plaza-Jennings, 2012), which are not easily quantifiable. Therefore, consideration and comparison of these different categories (and measurements) of costs in an analysis presents significant challenges. As such, we examine the price elasticity of demand using an exploratory case-specific approach in Section 4.5, rather than integrating costs into the econometric modeling. Estimated or anticipated incremental costs of HDV emissions regulations also vary by HDV class (Table A - 1); if the cost differential between

[5] The consumer price index was used to convert from nominal to real dollars. https://www.bls.gov/cpi/tables/supplemental-files/home.htm

classes is high enough, it may present incentives for class shifting by purchasers, as explored in Section 4.5.

Table 3. Example Estimated/anticipated Costs of HDV Emissions Regulations, 1985-2010, Nominal and Real (2019$) Dollars

Standard Year and Pollutant	**Source**	**Description of Cost/ Nominal Dollars**	**Estimated/Anticipated Costs***	
			Nominal	Real ($2019)
1985 NOx	U.S. EPA (1981)	Diesel trucks, Higher cost estimate (All components needed) (1980$)	$900	$2,788
		Diesel Trucks, Lower cost estimate, (intercooling/aftercooling not needed) (1980$)	$625	$1,936
		Diesel trucks, Average cost estimate (1980$)	$740	$2,292
		Fuel costs (losses per 1% fuel economy loss) (1980$)	$638	$1,976
1991 NOx	U.S. EPA (1985)	R&D NOx (1984$)	$44	$109
		Hardware NOx (1984$)	$113	$279
		Fuel Costs NOx (1984$)	$348	$860
1991 PM	U.S. EPA (1985)	Truck increased purchase price, PM (1984$)	$661	$1,633
		Fuel costs, PM (1984$)	$705	$1,741
		Fuel costs, PM, discounted (1984$)	$525	$1,297
1991, NOx and PM	U.S. EPA (1985)	NOX+PM, Total user costs for non-bus HHDDE (includes maintenance costs) (low) (1984$)	$1,050	$2,594
		NOX+PM, Total user costs for non-bus HHDDE (includes maintenance costs) (high) (1984$)	$1,180	$2,915
1994 - 1997, PM	U.S. EPA (1985)	Total PM User Costs, HHDDE w/ trap, Low (Includes first costs, and discounted fuel and maintenance costs) (1984$)	$838	$2,070
		Total PM User Costs, HHDDE w/ trap, High (Includes first costs, and discounted fuel and maintenance costs) (1984$)	$1119	$2,764
1998-2003 (Voluntary Clean Fleet Standards)	U.S. EPA (1994)	Increased engine costs to consumer, HDV, Diesel (1992$)	$477	$871
2004-2006 NOx	U.S. EPA (1997)	Total Cost (NPV) for HHDV in 2004-2005 (1995$)	$598	$1004
		Estimated increased purchase price for HHDV, 2004, NPV (1995$)	$467	$784

		Estimated increased operating price for HHDV, 2004, NPV (1995$)	$131	$220
2007 -2010 (Sulfur/PM/NOx)	U.S. EPA (2000)	Incremental System Cost (Hardware), HHDV, diesel, near term (2007) (1999$)	$3,230	$4,978
		Lifecycle Operating Cost (Fuel costs), HHDV, diesel, near term (2007) (1999$)	$4,626	$7,129
		Incremental System Cost (Hardware), HHDV, diesel, long-term (2012) (1999$)	$1,870	$2,882
		Lifecycle Operating Cost (Fuel costs), HHDV, diesel, long-term (2012) (1999$)	$3,979	$6,132

* As described by the U.S. EPA, HDVs are classified into the following categories: LHDDE, MHDDE, and HHDDE (Light, Medium and Heavy Heavy Duty Diesel Engine, respectively). LHDDE—Gross Vehicle Weight Rating (GVWR) of 8,500 to 19,500 lbs. and includes HDV classes 2b, 3, 4, and 5; MHDDE—GVWR 19,500 to 33,000 lbs., HDV classes 6 and 7; HHDDE—GVWR over 33,000 lbs., HDV classes 8a and 8b. Note that descriptions of classes (e.g. HDV, HHDDE, etc. and level of detail in use in EPA documentation (RIAs, etc.) have differed over time, and so may not necessarily align.

The 2004 HDV emissions standards specified a limit of NMHC+NOx of 2.4 g per brake-horsepower hour (g/bhp-hr), with an alternative standard of NMHC+NOx limit of 2.5 g/bhp-hr, and NMHC capped at 0.5 g/bhp-hr). The equipment expected to meet these limits included exhaust gas recirculation (EGR), advanced fuel injection and charge air systems. The standard was also expected to increase operating costs in the form of shorter oil change intervals, potential requirements for changes in oil systems and oil formulations, and additional requirements for emission control equipment cleaning and component replacement during engine rebuilds. Estimated costs to meet the standard varied by vehicle size, with Net Present Value (NPV) costs for heavy HDVs (HHDVs) estimated at about $470 (in 1995$), or about $780 in 2019$, as shown in Table 3 (estimated costs by HDV class are shown in Section 7.1 in the Appendix). Increased operating costs for HHDVs were estimated at about $130 (in 1995$), or $220 in 2019$. (EPA, 1997).

The 2007-2010 regulations, which are largely seen as the most extensive (and expensive) HDV emissions standards, involved two main stages: (1) increasingly stringent exhaust standards for new HDVs, phased in over the period 2007 to 2010, and (2) a switch to ultra-low sulfur diesel fuel for highway vehicles (EPA 2000). The specific standards under this rule were a PM limit of 0.01 g/bhp-hr, effective for the 2007 model year. Unlike the 2004 regulations, NOx and NMHCs were separated in this rule making, with standards for NOx of 0.20 g/bhp-hr; and for NMHC, 0.14 g/bhp-hr. The NOx and NHMC standards were phased in over the period 2007-2010 for diesel engines, with 50% of manufacturer sales required to meet the standard in 2007-2009, and 100% of sales required to meet the standard in 2010. For gasoline engines, 50% were required to meet the standard for 2008 model year, and 100% in 2009. For diesel HDVs, emissions reduction equipment expected to meet the standard included catalyzed diesel particulate filters for PM, and NO_x adsorber technology for NO_x. Selective Catalytic Reduction, or SCR, emerged as a primary compliance pathway, though one manufacturer reported using an advanced form of Exhaust Gas Recirculation, or EGR, for NO_x (Harrison and LeBel, 2012) . Higher-sulfur highway fuel could damage the emissions control devices, including catalysts in SCR systems which would not function as well in acidic environments created by high sulfur fuels inside the engine. Therefore, the use of ultra-low sulfur diesel fuel was required to meet the first part of the standard. The fuel standard portion of the rule required that, beginning September 1, 2006, fuel sold for use in highway vehicles model year 2007 and later have a sulfur content of less than 15 part per million (ppm).

The incremental system costs associated with the emissions control equipment required to meet the 2007-2010 standards for HHDVs were estimated at over $3,230 in the near term (in 1999$, or $4,978 in 2019$ dollars), declining to $1,870 ($1999) in the long-term ($2,882 in 2019$), as shown in Table 3 (with estimated costs by vehicle class shown in Section 7.1 in the Appendix). Increased lifecycle operational costs, which included the incremental cost of using ultra-low sulfur fuel and changes in service and maintenance costs for equipment, were expected to increase by over $4,600 (in 1999$) in the short-term (over $7,100 in 2019$); these costs were expected to decline slightly in the long-term (EPA, 2000).

The 2014 HDV standards for GHG emissions and fuel consumption differed from previous HDV emissions standards in that preceding HDV emissions standards tended to increase costs for purchasers and operators of HDVs. Emissions control technologies could increase vehicle capital costs, while also increasing operating costs by reducing fuel efficiency or requiring additional maintenance, among other factors. The 2014 standards, however, called for efficiency improvements to vehicles (tractors, for tractor-trailers) which increased upfront capital costs, but were expected to decrease operating costs—and significantly—for HDV owners and operators, in the form of fuel cost savings. Expected technologies and measures to meet the standard included improvements to engine components (e.g. reduced friction), aftertreatment systems, aerodynamic improvements, weight reductions, tire rolling resistance, speed limiters, and idle reduction technology. As reported in the Final Rule for Greenhouse Gas Emissions Standards and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles (2011): The incremental increase in average cost for combination tractors was estimated at just over $6,000 for model year 2014 model year (MY), declining slightly for 2015 and 2016 MY (~$5,900 and ~$5,700), and increasing again in 2017 MY to ~$6,400 (in $2009) with the Phase II standard. The improvements would result in estimated fuel savings of about 3% per year for 2014 MY, rising to 6% in 2017. Fuel efficiency improvements were expected to more than pay for themselves, and with short payback periods. As reported in the Federal Register Final Rule (2011), by 2018 MY, a combination tractor was expected to save over 3,200 gallons of fuel in the first year of operation, saving ~$10,600 in fuel costs (2009$), with efficiency improvements more than paying for themselves in the first year of operation alone—and with total net savings (fuel cost savings minus increased HDV costs) over a vehicle lifetime of seven years reaching ~$58,000 to ~$73,000 (depending on discount rate assumptions).

Whereas previous HDV emissions standards and regulations presented economic disincentives against purchasing HDVs post-standard, the GHG and fuel consumption standards may have provided an economic incentive to purchase HDVs. On the other hand, HDV purchasers may have noted that in later years, HDV fuel consumption standards were even greater than in 2014 and would result in even more fuel cost savings over a vehicle lifetime—while estimated incremental costs were expected to stay relatively stable or even decline—so there may have existed incentive to delay purchase of HDVs, if possible.

Table 4: EPA RIA projected incremental costs for control of air pollution from heavy heavy-duty vehicles (2019$)

Regulatory Period	Hardware	Operating Cost (NPV)	Total
2004	$784	$220	$1,004
2007	$4,978	$5,833	$12,107
2010*	$4,035	$5,833	$9,014

* Denotes costs in 2009

Analysis from ICCT (Posada, Chambliss, and Blumberg 2016) indicates incremental costs for the 2004 regulations were on the order of $1,421. Though ~41.5% greater, when considering the ongoing operations and maintenance costs of an HDV the ICCT estimate is on the same order of magnitude and reasonably well aligned with the initial EPA estimates. The ICCT report estimates control technology costs for the 2007 and 2010 regulations at $1,650 and $3,816 respectively.

Combined these estimates come to $5,466, which is well aligned with the EPA estimates, only about 9.8% higher, not including ongoing operational costs.

The ICCT report indicates that suggested retail prices have grown by around 1% per year since 2000. The largest year-over-year price increases occurred in 2013 (6%), 2006 (5%), and 2010 (4%). The largest drop was -2% in 2002, coinciding with the implementation of the 2004 NOx regulations by consent decree in October 2002.

As shown in Table 4, the projected costs associated with the 2007-10 regulations were considerably greater than for the 2004 regulations, implemented earlier in October 2002 by consent decree. Considering a heavy heavy-duty vehicle has a retail price of up to $150,000, these price increases are on the order of 1.9% - 3.3% on the hardware side of things, with an additional increase in ongoing O+M costs equivalent to ~4% of the purchase price in net present terms.

2.9 Conclusions from the Literature

This literature review has presented theory behind impacts of anticipated regulation on the trucking sector, and methods used in estimating the effects of changing prices on HDV sales. This review has also presented literature and empirical evidence surrounding impacts of anticipated regulation, specifically related to pre-buy and low-buy responses, key factors contributing to, or influencing HDV truck sales or activity, and factors influencing mode shifting between truck freight and other modes. Key findings of the review can be summarized as follows:

- Literature examining the effects of regulation on HDV sales is relatively sparse, and the studies and reports which have examined this issue have found widely varying estimates of pre-buy and low-buy, likely due to differences in methods and factors considered. The most recent and comprehensive work in this area, Rittenhouse and Zaragoza-Watkins (2018), estimated a spike in sales of ~31,000 HDVs in the months prior to the 2007 regulation, but found mixed evidence in response to other examined HDV regulations, including a modest pre-buy ahead of the 2004 regulations. Lam and Bausell (2007) estimate or point to more substantial (and negative) effects of HDV regulation, but also tend to use a less rigorous, and potentially biased approach of analysis. Even the most recent and comprehensive work in this area (Rittenhouse and Zaragoza-Watkins, 2018) performed no tests for stationarity and did not correct time series data for unit roots present in their data, suggesting there is room for improvement in terms of estimating effects of anticipated HDV emissions regulations in the United States.

- Responses of, or financial impacts on, trucking firms to increased costs may not always follow what would be expected by theory. For example, Dugan et al. (2017) found that firms with lower fuel efficiency (worsened fuel economy) in response to use of compliant engines actually saw a decrease in their operating ratios (lower ratio of expenses to revenue), which may be explained by an increase in fuel surcharges to freight customers. These findings suggest that trucking companies may pass on, and recoup (or more than recoup), certain costs, and that economic responses to HDV emissions regulations may be more complex than anticipated and may be counterintuitive in certain respects.
- Recent research and data have suggested that pre-buy and low-buy behaviors have taken place in other transportation sectors—for instance in Denmark in the passenger vehicle market, and in the maritime shipping sector in response to IMO Tier III standards.
- Several studies and reports have estimated the influence of key factors and drivers on HDV sales and HDV activity (whether directly or indirectly), and have indicated, in general:
    - Economic activity is key to HDV sales and HDV freight activity, though there is disagreement on the metric used (e.g. GDP, international trade), specific economic sectors considered, and the use of lag periods, among other factors. Research also indicates that the relationship of economic activity to trucking sector activity may be changing over time in response to a shift from production of goods to services. These findings suggest that economic activity and key characteristics of the economy may be important to consider in modeling HDV sales and activity.
    - Fuel prices have been found to be significant predictors of HDV sales and/or activity, though studies have differed in metric used (e.g. oil prices, diesel prices). Rittenhouse and Zaragoza-Watkins (2018) found oil to be a stronger predictor of HDV sales compared to diesel prices and also found a structural shift in the response of HDV sales to oil prices after 2001, suggesting that further exploration of the relationship between petroleum prices and HDV sales and activity are warranted.
    - Time of year and seasonality have also been shown to be of importance, as they capture effects of purchasing cycles on HDV sales, production and/or activity. Also, HDV production does not follow model-year production cycles, but rather

responds to orders by purchasers, on a several-month lag. These factors indicate the importance of incorporating seasonality and lags and understanding timing and definitions of HDV "sales" in seeking to model HDV sales over time.

    - Truck/HDV price or price index is, in several studies or reports, assumed to play an important role in HDV sales; the actual effects of truck price on sales at a macro level is unknown , however, suggesting that exploration of the impacts of truck prices on truck production and sales is warranted, in seeking to model and analyze HDV sales over time.
    - Truck freight activity/demand is also assumed to influence HDV sales in many studies/reports, though the actual relationship between these variables is unknown, suggesting that exploration of the influence of trucking freight activity on HDV sales is warranted.

- Mode-shifting from truck to rail or barge is generally not expected in response to moderate changes in costs, as different modes offer different attributes and are associated with their own constraints. Recent research has compiled a list of factors which influence mode choice, and which might encourage mode-shifting. These factors and trends (e.g. infrastructure investments, subsidies or regulations, fuel taxes, labor rules) may be important to consider in understanding trends in demand for trucking services, and related HDV sales.

The next phase of this work, detailed in the following sections, involves development of a method to project pre-buy and low-buy of HDVs in response to anticipated regulation, including examination of the influence of key factors and potential drivers of HDV sales, as identified in this review.

3 Data and Methodology

This section discusses the data and sources used in the analysis. All data series tested in the regression models are included, though not all are used in the final model specifications. We begin in Section 3.1 with discussion of the time series inputs we studied, then describe tests and treatments for stationarity in Section 3.2 in order to allow for robust model estimates. Section 3.3 discusses the modeling approach and Sections 3.4 and 3.5 discuss leading and lagging variables and coefficient interpretation, respectively.

Table 5: Summary table of variables used, models, units, and data sources

Variable	Models Used	Unit	Source
Truck Sales (Classes 6, 7, and 8)	Dependent variable in all models	Δ log Monthly Sales	(Wards Intelligence 2020)
GDP	All models	Δ log GDP (billions of dollars)	(BEA 2020b)
Brent Oil Price	Models 2, 3, 4	Δ log Brent Oil Price ($/bbl)	(EIA 2020)
Total Imports and Exports	Model 3	Δ log Total Imports + Exports (billions of dollars)	(BEA 2020c) and (BEA 2020a)
Consumer Sentiment	Model 4	Δ log Consumer sentiment (Index 1966Q1 = 100)	(University of Michigan 2020)

3.1 Time Series Inputs

3.1.1 Truck Sales Data

This section discusses monthly heavy-duty truck (Classes 6, 7, and 8) time series sales data (Wards Intelligence 2020). Figure 2 shows monthly Class 6, 7, and 8 truck sales from 1990 through 2018. These data exhibit significant volatility, particularly Class 8 sales, which show a high of 26,462 in December 2006 prior to the Great Recession, and a low of 6,236 in February of 2009 toward the end of the recession. Inter-annual volatility is lower for Class 6 and 7 vehicle sales, though we do see a shift in the proportional share of Class 6, 7, and 8 vehicle sales between Class 6 and 7 vehicles. Earlier in the time series the relative share of Class 7 vehicles grew from ~2x to ~7x Class 6 sales in 1998, before declining to close to a 1:1 relationship between Class 6 and Class 7 sales post-2004.

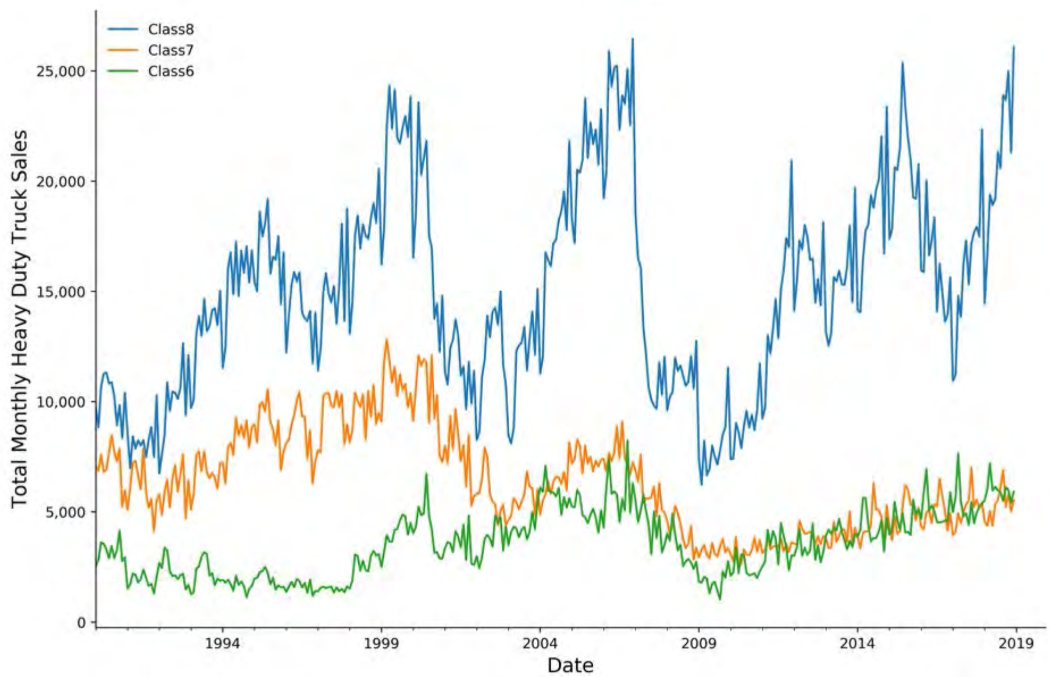

Figure 2: Class 6, 7, and 8 heavy duty truck sales by month (Ward's Automotive)

Monthly Class 8 sales are weakly and positively correlated with both Class 6 (Person's r = 0.544) and Class 7 (Pearson's r = 0.388) monthly sales (Table 6), as expected, given that heavy-duty truck sales are likely responding to the same, or similar, macroeconomic factors. Monthly Class 6 and 7 truck sales are not correlated (Person's r = -0.095), though the first difference of the logs of the two time series is weakly and positively correlated (Table 7).

Table 6: Pearson's R Correlation Coefficient between monthly class 6, 7, and 8 truck sales post-1990

	Class 8	**Class 7**	**Class 6**
Class 8	1.000	0.388	0.544
Class 7	0.388	1.000	-0.095
Class 6	0.544	-0.095	1.000

Table 7: : Pearson's R Correlation Coefficient between the Δlog monthly class 6, 7, and 8 truck sales post-1990

	Class 8	**Class 7**	**Class 6**
Class 8	1.000	0.560	0.460
Class 7	0.560	1.000	0.522
Class 6	0.460	0.522	1.000

Figure 3 shows boxplots of monthly heavy duty truck sales for Classes 6, 7, and 8. Class 8 sales, on the left, show relatively stable sales from March through October, followed by a dip in November and an increase in December. January and February are the two slowest months for Class 8 sales. Class 7 sales (middle) are strongest in March through August and decline towards the end of the year. Class 6 sales also generally peak around March, with weaker sales during the winter months.

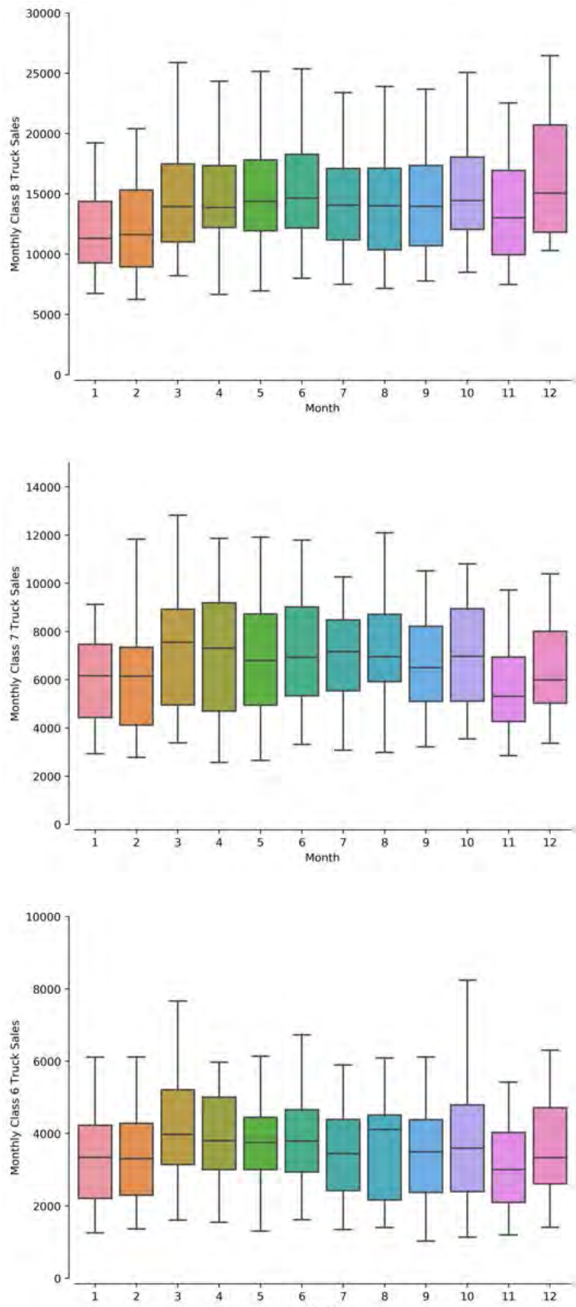

Figure 3: Boxplot showing sales by month for Class 8 (top), Class 7 (middle), and Class 6 (bottom) heavy-duty vehicles

Figure 4 shows year over year growth in heavy duty vehicle sales. Classes 8 (top panel) and 7 (middle panel) show similar cyclical patterns, rising and falling at similar times. The effect of recession

Figure 4: Year-over-year percent change in monthly sales for Class 8, 7, and 6 heavy duty trucks

periods in the early 2000s and the great recession in 2007-2009 are clearly visible in both data series. Class 6 also follows a similar pattern, though the cyclical pattern is generally weaker than for Class 7 and 8. Class 8 sales show strong cyclical patterns where sales rise and fall year over year in well-defined groupings. Patterns in year over year sales differences in Class 7 are not as strong.

3.1.2 Gross Domestic Product (GDP)

Gross domestic product (GDP) is a measure of the total economic productivity of the economy, measured as the "adjusted value of the goods and services produced by labor and property located in the United States." (Figure 5) (BEA 2020b). GDP gives an indication of the overall health of the economy, measuring total economic productivity. In times when productivity goes up, the economy is expanding, and we would anticipate greater consumption of materials transported by truck. In times when GDP decreases, the economy is contracting, or in a recession, and we would anticipate reduced consumption of good and services.

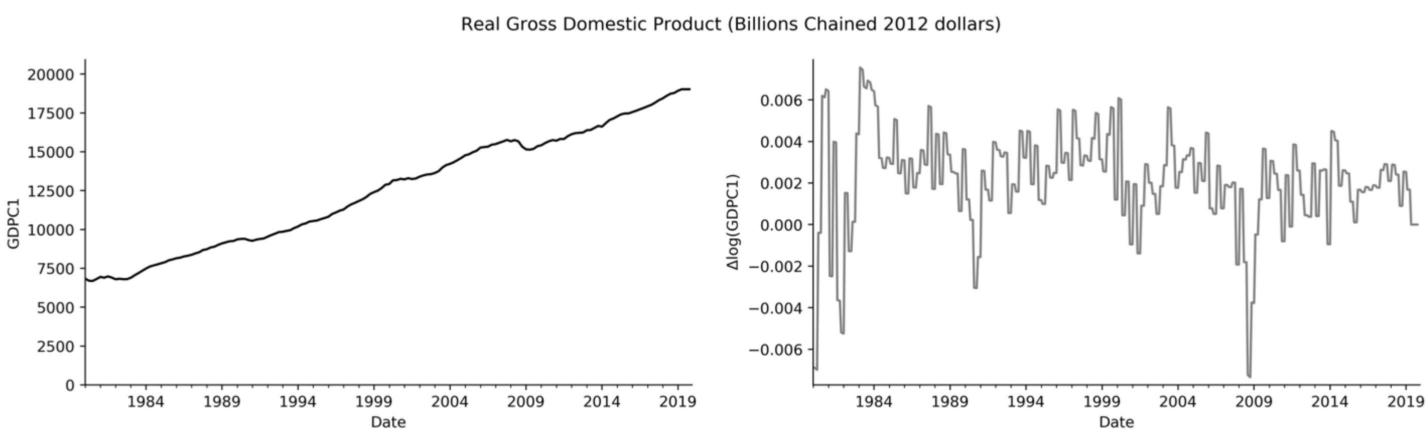

Figure 5: Time series showing quarterly GDP and the log of first differences (BEA 2020b)

3.1.3 Brent Oil Price

GDP is not the only driver of trucking sales and activity. Accordingly, we add in Brent Oil prices (Figure 6) (EIA 2020), again following the approach outlined by Rittenhouse and Zaragoza-Watkins (2018). The intuition behind adding fuel price into the regression is that because fuel comprises such a large fraction of the operating costs (21-39% over the past ten years),[6] fleet managers may reduce purchases in times when prices are high or shift to more fuel efficient vehicles. One reason could be that they reduce miles traveled, and therefore increase longevity of the vehicle – although Winebrake et al. showed that these rebound effects do not really exist in the HDV sector. They also might switch to fuel efficient vehicles, but that might ultimately encourage more new vehicle purchases.

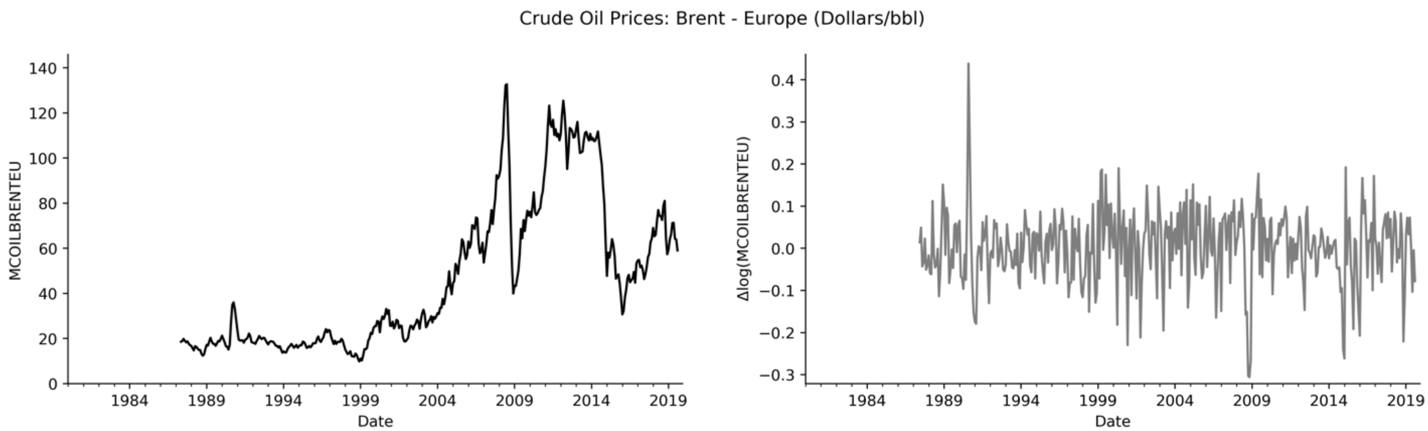

Figure 6: Time series showing monthly Brent crude oil spot prices and the log of first differences (EIA 2020)

Based on previous work in this area, we do not expect fuel prices to have a significant impact on HDV purchases. Although fuel prices represent 21-39% of the operating expenses of trucking fleets, these prices are often passed along to consumers in the form of fuel surcharges. There is some theory that would suggest that fleet operators may purchase more efficient (potentially newer) vehicles when fuel prices are high – but this effect would be modest, since a vehicle purchase is a major investment. Fuel prices also affect everyone in the sector, and so there is no competitive advantage for changing behavior. Given the ability to pass along higher fuel costs as surcharges and the fact that changing prices affect the whole sector, fuel prices are more likely to have an effect on operational decision making rather than capital purchases. Furthermore, while surcharges would increase the cost of shipping and thus the delivered price of goods, demand would be heavily driven

[6] https://truckingresearch.org/wp-content/uploads/2019/11/ATRI-Operational-Costs-of-Trucking-2019-1.pdf

by the price elasticity of demand for the final delivered good. Winebrake et al. (2015b) have shown that rebound effects related to fuel price changes are minimal.

3.1.4 Producer Price Index – Trucks

The PPI for trucks greater than 33,000 lbs GVW (PPI-Trucks) is shown in Figure 7, overlaid on recessions (grey bars) and the regulatory timing of NOx regulations (black lines) and other vehicle emission standards (dotted lines).

The PPI-Trucks (U.S. Bureau of Labor Statistics 2020) is similar to other producer price indices, in that it tracks the selling prices received by domestic producers, accounting for goods, services, and other products used as inputs to the production of the good measured. The PPI-Trucks is calculated from the first commercial transaction and does not account for secondary sales. The PPI-Trucks is indexed (June 1987 = 100) and so accounts for real changes in producer prices, without adjusting for inflation. As such, some of the steadily increasing trend shown in Figure 7 is attributable to inflation effects, while other changes in the PPI_Trucks are subject to macroeconomic, regulatory, and trade effects.

Inspection of the curves suggests a regime shift in the PPI in 2002, corresponding to the early implementation of the 2004 regulations, and in the few months post-2007, and 2010 regulations going into effect. Regime shifts appear in the PPI as large step-wise shifts in PPI. As PPI is normalized, these step-wise changes indicate a shift in price that is outside of the typical trend in increasing PPI. The shifts in PPI are further illustrated in the bottom panel of Figure 7, which shows the month-over-month change in PPI. These data show clear spikes, i.e. step-wise increases in the PPI that are greater than the general noise in the data, in late 2002, early 2007, and early 2010.

These insights are supported by the changepoint detection analysis shown in Figure 8. The PPI trucking time series was analyzed using the Ruptures[7] package and three different change point detection algorithms, Pelt, dynamic programming, and binary segmentation. Changepoint detection programmatically looks for breaks in the time series, where changes in the probability distribution of a time series changes. As such, change point detection algorithms can be used to identify unknown shifts in the data, or statistically confirm possible shifts in the time series.

[7] Changepoints were estimated using the Ruptures python package. Documentation available at https://centre-borelli.github.io/ruptures-docs (Truong, Oudre, and Vayatis 2020)

Though the different changepoint detection algorithms do identify slightly different sets of changepoints, each algorithm independently identifies common regime shifts in the PPI-Trucks corresponding to the 2007 and 2010 enforcement periods.

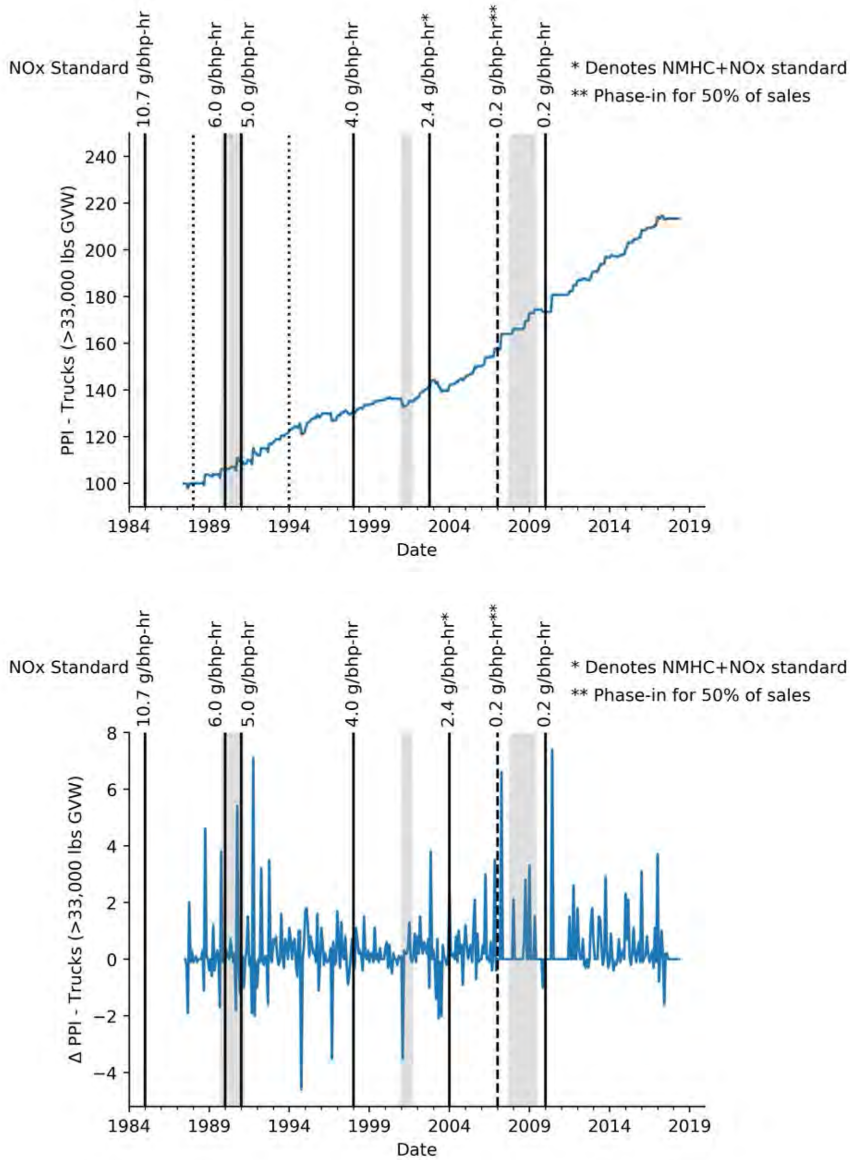

Figure 7: (Top panel) Producer Price Index for trucks greater than 33,000lbs GVW from 1985 to present (1985 = 100). Grey bars show recessions, vertical black lines show vehicle NOx emission regulations, vertical dotted lines show other vehicle emission regulations. (Bottom Panel) Month over month change in producer price index for trucks greater than 33,000lbs GVW from 1985 to present.

Notably, the changepoint algorithms also identify a shift in the PPI-Trucks in mid-2002. This changepoint corresponds to the enforcement of the planned 2004 NOx rules in October of 2002 by consent decree, identified in the literature as having an effect on the production of heavy-duty trucks (Lam and Bausell 2007; Rittenhouse and Zaragoza-Watkins 2018).

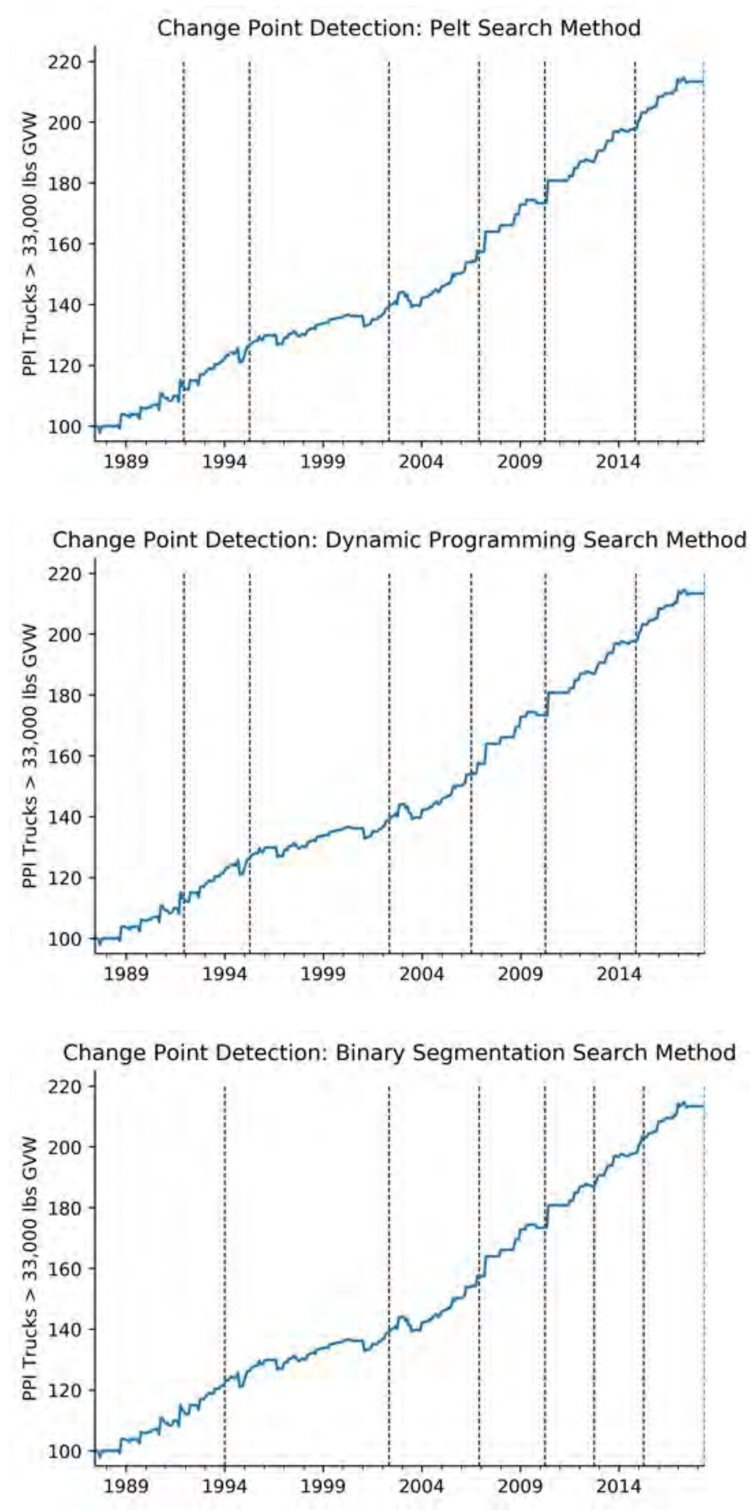

Figure 8: Change point detection methods identifying breakpoints in the PPI-Truck time series data

The 2007 changepoint occurred in April of 2007, when the PPI-Trucks jumped from 157.4 to 164, an increase of 4.2%. In June of 2010, the PPI-Trucks jumped 4.3% from 173.4 to 180.8. In total, from the last period before the shift in 2007 to the first period after the shift in 2010 the PPI-Trucks jumped 14.4%, the largest range in a time window of that size in the available dataset (post-1985).

We would expect there to be a negative and important relationship between HDV prices and HDV purchases. Further, we might expect there to be a lag between the PPI-Trucks and the HDV purchase, as anticipated rises in costs affect purchasing decisions. [Note: PPI-Truck represents data at "time of delivery."] Thus, we would expect HDV sales (which are influenced by the price of the vehicle at the time of order) to lag the actual PPI (which represents the price of the vehicle at the time of delivery). Industry data show that the average length of time between a truck order and delivery is 2-5 months[8], which corresponds to the lag observed between Class 8 purchases and the PPI-Trucks.

Given the high relative costs of HDV vehicles, we also do not expect much of a pre-buy effect, as any advantage associated with increasing early purchases because of anticipated HDV price increases are offset by the costs of managing excess vehicle capacity, which can be expensive, or selling or scrapping older stock.

3.1.5 Imports and Exports

Nearly all goods in the United States travel by heavy-duty truck over at least some portion of their journey. As such, the intuition behind considering imports and exports as an explanatory variable for truck purchases is that increases in imports and exports will increase demand for heavy-duty trucking in order to move goods between their origins and destinations within the country. As the trucking industry is somewhat agnostic as to whether a good is being imported or exported, we combine imports (Figure 9) and exports (Figure 10) into a single variable, total imports and exports, for modeling purposes.

As shown in Figure 9 and Figure 10, imports and exports in the U.S. follow similar patterns, though the U.S. is generally a net importer of goods. The data for both time series are generally increasing, with notable dips in the early 2000s, corresponding to the bursting of the dot-com bubble, and in 2008-2009, corresponding with the great recession.

[8] https://www.wsj.com/articles/get-in-line-backlog-for-big-rigs-stretches-to-2019-1534500005

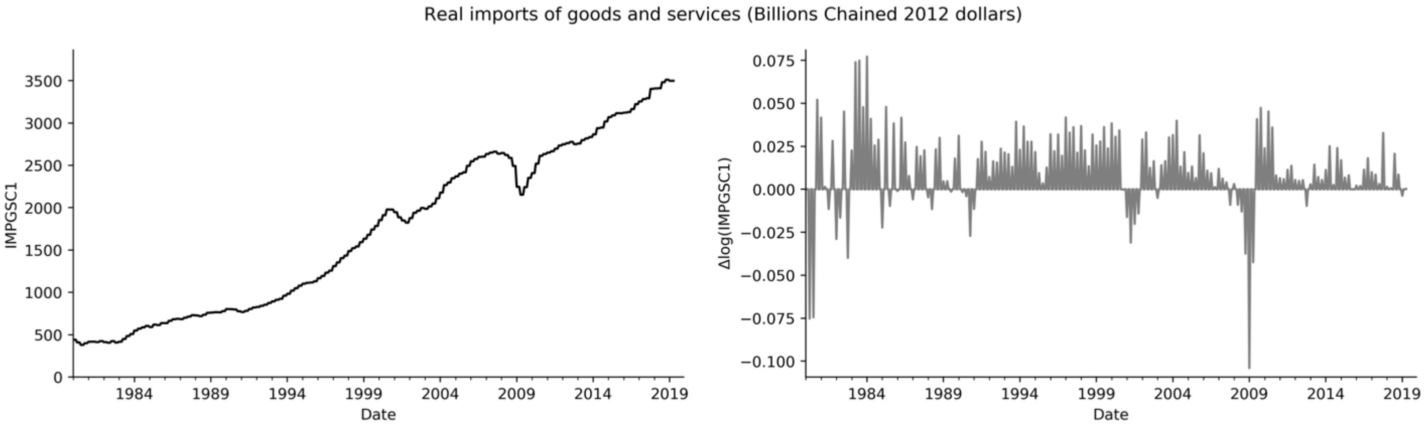

Figure 9: Time series showing monthly imports and the log of first differences (BEA 2020c)

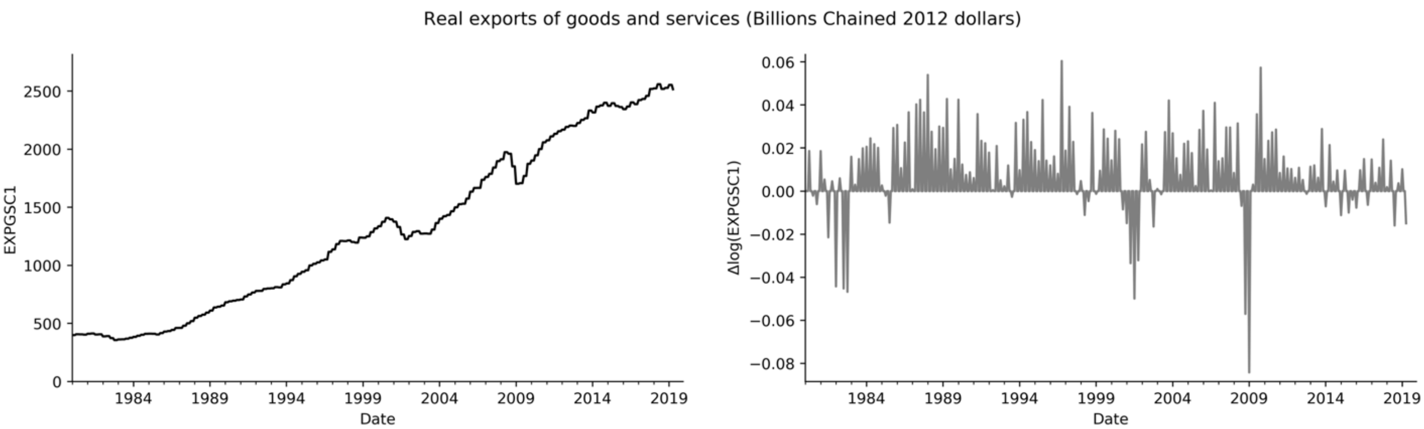

Figure 10: Time series showing monthly exports and the log of first differences (BEA 2020a)

3.1.6 Consumer Sentiment

Consumer sentiment, derived from the University of Michigan's monthly Survey of Consumers (University of Michigan 2020) is considered to be a useful indicator of the future course of the national economy. Consumer sentiment is measured using a survey of around 500 consumers, containing 50 questions in three main areas: personal finances, business conditions, and buying conditions. The consumer sentiment index (Figure 11) is closely correlated with macroeconomic indicators including interest rate movements, changes in unemployment, inflation, GDP, and light-duty vehicle sales, leading the latter by ~2 quarters with a correlation coefficient of 0.73.[9] Given the

[9] https://data.sca.isr.umich.edu/fetchdoc.php?docid=24774

efficacy of the consumer sentiment index for describing other macroeconomic conditions, we test whether consumer sentiment may also be a useful leading indicator for heavy-duty truck sales.

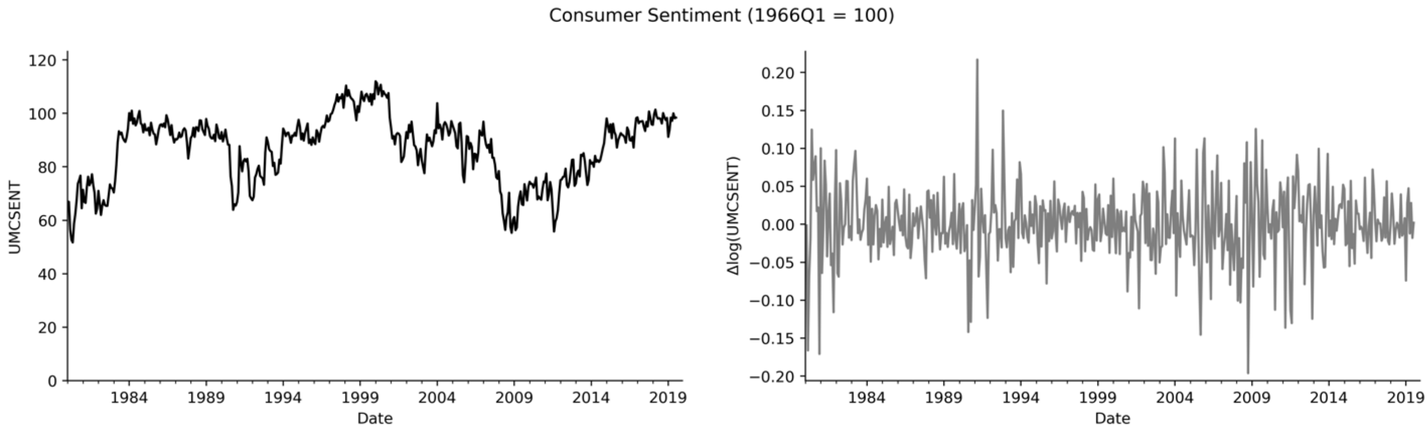

Figure 11: Time series showing consumer sentiment and the log of first differences (University of Michigan 2020)

3.1.7 Other Time Series Tested

Exploratory analysis was also conducted on the following time series, which were ultimately not included in the final model as they were either non-significant, reduced the explanatory power of other variables while not improving model fit, or introduced collinearity issues.

- Truck Tonnage
- All Employees, Truck Transportation
- Industrial Production: Durable Goods: Heavy duty truck (includes Classes 6-8)
- Producer Price Index by Industry: Tire Manufacturing (Except Retreading): Truck and Bus (Including Off-The-Highway) Pneumatic Tires
- Value of Manufacturers' Total Inventories for Durable Goods Industries: Transportation Equipment: Heavy Duty Trucks

Exploratory analysis indicated that truck employees and industrial production of heavy-duty trucks may be significant indicators in OLS regression. Time series graphs for these data series are shown in Figure 12. As seen, these two indices do track together, though lagged slightly, and with the employees time series showing less volatility than the production index. Pearson correlation coefficients for the first difference in the logs for Class 8 truck sales, truck production index, and truck transportation employment are shown in Table 8. As shown, all three of these measures are uncorrelated with one another.

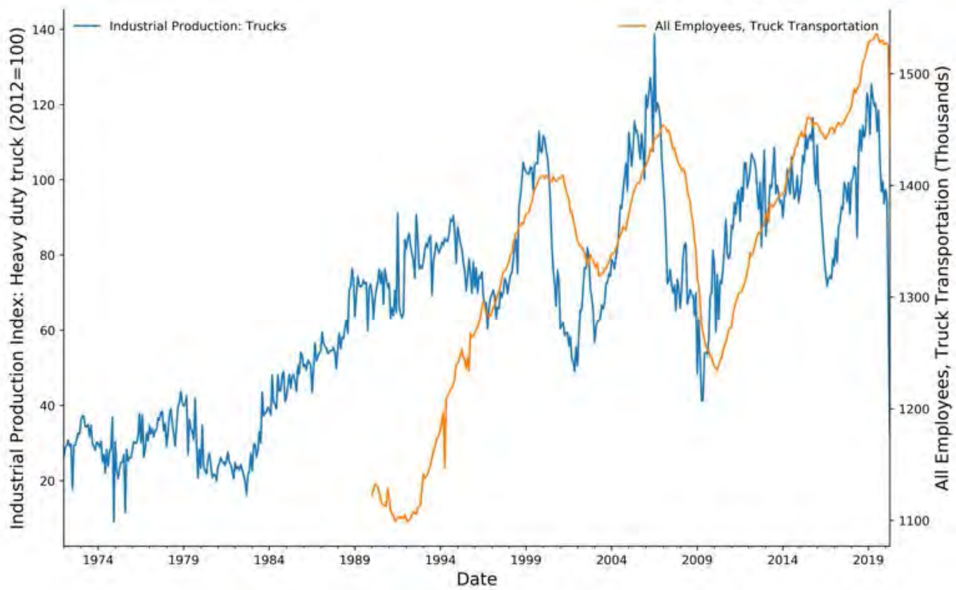

Figure 12: Time series showing industrial production index for heavy duty trucks (left, blue) and employees in the truck transportation sector (right, orange)

Table 8: Pearson correlation coefficients between the difference of the logs of class 8 truck sales, truck production index, and truck transportation employment

	Class 8	**Truck Production**	**Truck Employment**	**GDP**
Class 8 Sales	1.0000	0.1543	0.0977	0.1306
Truck Production	0.1543	1.0000	0.0689	0.1365
Truck Employment	0.0977	0.0689	1.0000	0.1914
GDP	0.1306	0.1365	0.1914	1.0000

Exploratory analysis shows that including truck employment in the regressions reduces the explanatory power of GDP, rendering the coefficient non-significant, while also being non-significant itself. One possible explanation for this is that truck employment is more correlated with GDP than the other variables, and truck employment may also be more a function of other macroeconomic forces that may interact differently with the sales of class 8 trucks.

3.2 Testing for Unit Roots

This section shows the results from augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to determine the presence of unit roots (nonstationarity) in our data. Testing for non-stationarity is important when performing time-series analysis as this may produce spurious regression coefficients, and long-run equilibrium relationships may exist among the data series, which may be cointegrated and require adjustment of the models to account for cointegration (Winebrake et al. 2015b; Wang and Lu 2014; Hamilton 1994; Enders 2004).

It is common in the literature to perform both a KPSS and an ADF test when testing for stationarity and unit roots. The ADF test is performed to test for unit roots, while the KPSS test looks for stationarity. By testing for unit roots and stationarity we are able to identify series that are stationary, or series that have a unit root, or series that provide insufficient information to make a determination. If both the KPSS and ADF tests indicate the presence of non-stationary data with a unit root we can be confident that unit roots are present. Similarly, if the tests do not show that unit roots are present post-correction, we can be confident that the corrections made the data stationary.

The results indicate the presence of unit roots with our non-transformed data, but that these unit roots disappear after a first order differencing process, thereby establishing stationary data that can be used in a first order difference model.

3.2.1 Augmented Dickey-Fuller Test

We first tested for unit roots of our untransformed and natural log transformed data using an augmented Dickey-Fuller (ADF) test. In an ADF test, the null hypothesis is that there is a unit root for the series and the alternative hypothesis is that there is no unit root for the series (the series is stationary). The p-value represents the risk of rejecting the null hypothesis while it is true. The results are shown in Table 9. One can see that for our untransformed variables, we find it difficult to reject the null hypothesis for most of our variables, and hence the results indicate the presence of unit roots. We next took first differences of our variables and retested. Those results are also shown in Table 9.

After taking first differences, we are able to reject the null hypotheses for all data series. Additionally, taking the log difference also allows us to reject the null hypothesis. Therefore, we have partial confidence that our first difference and log-difference transformed data series removed the unit root. Taking the log difference is useful for modeling purposes as it allows us to interpret the coefficients directly as elasticities.

Table 9: Results of the ADF test results for the natural log transformation of the original data and the data after a first order difference transformation.

	ADF Statistic (Uncorrected)	p-value	ADF Statistic (First Difference)	p-value	ADF Statistic (Log Difference)	p-value
Real Gross Domestic Product (Billions Chained 2012 dollars)	0.0572	0.9630	-4.7931	0.0001	-4.7248	0.0001
Consumer Sentiment (1966Q1 = 100)	-3.5429	0.0070	-10.3067	0.0000	-10.7016	0.0000
Crude Oil Prices: Brent - Europe (Dollars/bbl.)	-2.0683	0.2575	-13.3543	0.0000	-9.3790	0.0000
Producer Price Index: Heavy Duty Truck Manufacturing (>33,000 lbs)	1.0467	0.9947	-5.5862	0.0000	-5.5729	0.0000
Wards Class 8 Vehicle Sales	-3.2684	0.0164	-4.6973	0.0001	-4.5778	0.0001
Total Imports + Exports	0.4328	0.9827	-6.8246	0.0000	-7.1550	0.0000

3.2.2 KPSS Test

We then performed a KPSS test to support the results of the ADF test. We tested two specifications of the KPSS test where we first assumed the data were stationary around a constant, then we tested that the data are stationary around a trend. Results (Table 10) were similar between the two specifications and as the plots in Section 3.1 indicate the presence of a trend in most series, we only present the results testing for stationarity around a trend.

Table 10: Results of the KPSS test for the natural log transformation of the original data and the data after a first order difference transformation

	KPSS Statistic (Uncorrected)	p-value	KPSS Statistic (First Difference)	p-value	KPSS Statistic (Log Difference)	p-value
Real Gross Domestic Product (Billions Chained 2012 dollars)	0.2375	0.0100	0.1047	0.1000	0.0931	0.1000
Consumer Sentiment (1966Q1 = 100)	0.2721	0.0100	0.0583	0.1000	0.0548	0.1000
Crude Oil Prices: Brent - Europe (Dollars/bbl.)	0.2623	0.0100	0.0488	0.1000	0.0522	0.1000
Producer Price Index: Heavy Duty Truck Manufacturing (>33,000 lbs)	0.6883	0.0100	0.0749	0.1000	0.0770	0.1000
Wards Class 8 Vehicle Sales	0.1307	0.0784	0.0262	0.1000	0.0273	0.1000
Total Imports + Exports	0.4916	0.0100	0.0534	0.1000	0.0994	0.1000

Note: KPSS test outputs for p-values greater than 0.1 are shown as p = 0.1

H_0 for the KPSS test is that that data are stationary around a trend. In that case we are able to reject the null for all variables, except truck sales, indicating that these data are non-stationary. Correcting the data to use first differences and the first difference of the logs we cannot reject H_0 for all variables, indicating that these series are stationary post-correction.

The KPSS results, taken with the ADF results suggest that by performing these transformations we are confident that any unit roots present have been removed and that the data are now stationary. As the data are corrected for stationarity and unit roots, tests for cointegration are not necessary.

3.3 Econometric Framework: Time Series Modeling Approach

We test for pre-buy and low-buy effects using a time series modeling approach, employing binary indicator variables corresponding to the periods 1-12 months either side of regulations going into effect. This approach is similar to that taken by Rittenhouse and Zaragoza-Watkins (2018) and the U.S. General Accounting Office (GAO 2004). The 12-month period either side of regulation is consistent with prior studies, including Rittenhouse and Zaragoza-Watkins (Rittenhouse and Zaragoza-Watkins 2018). This analysis extends the period of analysis beyond that previously studied, from 8 months to 12 months, in order to ensure that any low-buy or pre-buy behaviors in the tails are being captured. Additionally, this approach is consistent with annual cycles in vehicle purchasing and model year updates.

As month of year fixed effects (Bertrand, Duflo, and Mullainathan 2004) and other macroeconomic factors are controlled for, the coefficients on these indicator variables will therefore represent the anticipatory effect of pending regulations, and the residual effect after regulations go into force. Although differencing the time series data remove unit roots, as discussed in Section 3.2, seasonal patterns are persistent in the data after differencing, which need to be controlled for in order to obtain unbiased estimates.

We test these indicator variables using four forms.

1. First we specified a unique variable for each single month pre- and post-regulation, considering all regulations combined in the study period. This model specification tests for the presence of a general response to regulation, without identifying the specific response to individual regulations.
2. Second, we specified a variable for the period *m* combined months pre- or post-regulation, again considering all regulations combined in the study period. In this format, Pre_1 would

correspond to the single month prior to regulation, and Pre_2 would correspond to the period two combined months prior to regulation, all regulations taken together, and so on until Pre_{12} which would include all 12 months prior to the regulation.

3. Third, as with form 1, we specified a variable for each individual month in the 12 months before and after regulation, but modeled results for each regulation individually. This specification allows us to test for the effects of specific regulatory periods.
4. Fourth, as with form 2, we specified a variable for the period *m* months combined pre- and post-regulation, for each individual regulation in the study period.

Upon inspection, form 4, where regulations were treated independently and months were grouped together provided the most significant results, and was the model form used going forward, unless otherwise specified.

3.4 Leads and Lags

We specify the models as such based on the following observations from industry:

1. Orders are placed based on binding quotes from manufacturers. These quotes are based on actual production costs, profit margins, and discounts. Manufacturers need to think about production costs in terms of current and future costs, since the production process can take 2-6 months.

2. There is a 2-6 month lag between order and delivery. The lag is a function of demand and production capacity. During periods of high demand, production lags can be long.

3. The demand data (i.e., purchases for a given month) represent actual *deliveries* of HDVs. These vehicles would have been ordered 2-6 months previously, depending on the production time needed.

We assume that the buyer is anticipating higher production costs for manufacturers *in the future* and fears prices for vehicles will increase when the regulation goes into effect. The buyer wants to take possession of the HDV before these higher production costs are manifested in the price. Thus, the buyer makes an *anticipatory purchase decision* (much like an investor makes a decision to buy or sell an equity in anticipation of future price movements). The manufacturer quotes prices to the buyer based on costs at time of delivery, i.e. the delivered price. The model also assumes the buyer has *reliable* information about future production cost trends (the statistical significance of this model will shed light on how reliable such information is). A simplified (linear/non-differenced) model can be structured as Equation 1.

Equation 1

$$D_t = \alpha + \beta \cdot P_{t+m}$$

where, D_t represents demand (delivery) of HDVs in month t; P_{t+m} represents the anticipated price m months in the future from the time of delivery. We include GDP as a leading indicator to represent the strength of the economy at the time of purchase, testing for the most statistically significant lead times.

3.5 Coefficient Interpretation

With the exception of indicator variables (0 or 1) used to describe periods around regulations for the differences in differences modeling, the OLS models are specified based on the first difference of the logs of the time series variables. As the models use the difference in the logs, the coefficients determined may be interpreted as elasticities, with the exception of the coefficients on indicator variables, which are not logged (log(1) = 0)[10]. The first difference log-log model specification follows the form

$$\ln Y_t - \ln Y_{t-1} = \alpha + \beta \cdot (\ln X_t - \ln X_{t-1})$$

Otherwise written as

$$\Delta \ln Y = \alpha + \beta \cdot \Delta \ln X$$

In this example Y represents the sales for a class at time t, and X represents a vector of independent variables, discussed in more detail in Section 4.2, at t. This first difference equation is often used to address unit roots (i.e., to convert non-stationary data to stationary data), as discussed in section 3.1.7. In this equation, β represents the change in the first difference of the natural log of Y for a one-unit change in the first difference in the natural log of X. Since for small (~ ± 20%) Δln(Y) and Δln(X), Δln(Y) and Δln(X) can be approximated as the percent change of Y and X respectively, we have the following equivalent equation:

---

[10] The coefficient on the indicator variable, which is not logged, is the percent change in Y due to the presence of the indicator variable (i.e. when var = 1).

$$\%\Delta Y = \alpha + \beta \cdot \%\Delta X$$

Therefore, the coefficient β represents the "change in the percentage change" in Y for a one-unit "change in the percentage change" of X, that is, the coefficient β is the elasticity of Y with respect to X.

In the case of the indicator variables, the model follows a log-linear form, simplified as follows

$$\Delta \ln Y = \alpha + \beta \cdot X$$

This equation includes a first difference of the natural log of Y, but a linear relationship with X. In this equation, β represents the change in Δln(Y) for a one-unit change in the value of X, i.e. the indicator variable is on (1) or off (0). For small ΔY, Δln(Y) approximates the percent change in Y, so the equation can be rewritten as

$$\%\Delta Y = \alpha + \beta \cdot X$$

Therefore, the coefficient β represents the change in the percentage change in Y for a one-unit change in the actual value of X.

Further discussion of the coefficient interpretations discussed here is available in Winebrake et al. (2015a). One limitation of this approach is that it assumes constant elasticities. While in some instances this assumption may be problematic, over large price changes for example, the changes in vehicle price, and other factors associated with the regulation, are likely small and therefore the assumption of constant elasticities is reasonable.

4 Results and Discussion

We present results iteratively. We begin by testing for month of year fixed effects, then we add in variables and test for leading and lagging indicators. Finally, we discuss the working model, and interpret the coefficients. Note that throughout this section, the text will generally refer to sales data. In fact, these data are based on date of delivery, not the original date of order. Data on date of order were not available for this study, therefore we use date of delivery as a reasonable proxy for date of order, with the important caveats discussed in section 3.4.

4.1 Month of Year Seasonality

Plotting of the sales data (Figure 3) shows cyclical patterns in the sales time series. Boxplots of the data grouped by month indicate that sales follow seasonal patterns with January and February showing the fewest sales, and October – December showing the highest sales. As such, we begin with a simple regression checking for evidence of seasonality in the vehicle sales data post-2000 with the following regression, described in Equation 2.

Equation 2

$$\Delta \mathrm{logSales}_{\mathrm{it}} = \beta_1 \mathrm{Month}_t + \epsilon$$

Where the change in the log of truck $\mathrm{Sales}_{\mathrm{i}}$ (where i = Class 7 or 8) in month t (from month_{t-1}) is simply a function of the month of year and the error term, i.e. controlling for month-of-year fixed effects. Month of year is encoded such that the categorical month of year (January, February, etc.) is translated into a set of 12 binary variables, each representing one month, i.e. for a given month only that month will be represented by a 1, and all other months will be 0.

The month-of-year coefficients for Classes 7 and 8 vehicle sales are shown in Table 11 (Class 6 data are available in the appendix). As shown, controlling for month-of-year fixed effects across the different classes is important as a number of months show significant coefficients across the classes. Similar patterns persist across classes, where January sees a significant reduction in truck sales, followed by a significant uptick in March (February for Class 6). The end of the year sees significantly increased sales in October, followed by a decrease in November, and a large increase in December. Subsequent regression models show that month of year fixed effects are robust to model specification, therefore for the purposes of brevity we omit the fixed effects coefficients from subsequent regression tables. The inclusion of the intercept in subsequent OLS regression models does not affect the coefficients but moves the Month = 1 (January) coefficient to the intercept.

Table 11: Month-of-year fixed effects for Class 7 and 8 vehicle sales

Month	Δlog Class 8	Δlog Class 7
January	-0.2895***	-0.0719***
February	0.0187	-0.0079
March	0.1816***	0.1723***
April	0.0108	-0.0367
May	0.002	-0.0282
June	0.0463***	0.0547***
July	-0.0686***	-0.0211
August	-0.0034	0.0292
September	0.0048	-0.105***
October	0.0661***	0.0966***
November	-0.1248***	-0.2134***
December	0.1795***	0.1152***
Adj. R^2	0.648	0.406

4.2 Iterative Modeling: Testing Variables

For the ease of the reader, iterative testing of model variables is presented separately by heavy-duty class, beginning with class 8 vehicles followed by Class 7. Model specifications follow the form outlined in Equation 3, where i represents Class 7 or 8 vehicle sales, and t represents the month of year. Exploratory analysis found that Class 6 HDVs were not as well explained by the models describing Class 7 and 8 trucks. One possible explanation for this is that Class 6 vehicles include a wide range of vehicle types, including school buses, beverage trucks, and single-axle box trucks that may be described by a different set of economic variables than those which describe Classes 7 and 8, which are dominated by freight hauling heavy-duty semi tractors. For the interested reader, results related to Class 6 sales, using the same model specification used for Class 7 and 8, may be found in the Appendix.

Iterative modeling focuses on class-level analysis and does not take into account manufacturer.

Equation 3

$$\Delta log\, Sales_{i,t} = \alpha + \beta_{1,t} Month_t + \beta_{j,t} \Delta \log X_{j,t} + \varepsilon_t$$

Where X represents the set of independent regression variables modeled, as discussed in section 3.1. These variables include:

- Δ log GDP, leading by one month, i.e. Δ log GDP_{t-1}
- Δ log Brent Oil Price in month t
- Δ log Total Imports and Exports in month t
- Δ log Consumer sentiment in month t

Exploratory analysis of the PPI for HDV trucks yielded collinearity issues with other variables with greater explanatory power and is therefore omitted from the analysis.

4.2.1 Class 8 Trucks

Table 12 shows OLS regression coefficients for iterative model specifications for class 8 trucks. Having identified and controlled for seasonal variation in Class 8 truck purchases we then expanded the regression model to include additional variables identified as potential influencing factors based on the theory of purchasing decisions and literature review. We begin by adding GDP, shown in Model (1), identified as an important factor by Rittenhouse and Zaragoza-Watkins (2018). As a reminder, we are regressing the difference in the logs of Class 8 sales and GDP, therefore the subsequent regression coefficients can be interpreted as elasticities. The results of regression 1 show that Class 8 purchasing decisions are positive, elastic, robust and significant with respect to GDP. From regression 1, we see that a 1% increase in GDP corresponds to a 5.14% increase in Class 8 truck sales.

Table 12: Iterative model specifications for class 8 trucks

	(1)	(2)	(3)	(4)
GDP	5.1433**	5.2841**	4.123*	4.119*
Brent Oil[11]		-0.0635	-0.0698	-0.0698
Total Imports and Exports			0.5784	0.5782
Consumer sentiment				0.0014
Adj. R2	0.651	0.652	0.652	0.651

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

[11] Combinations of aggregated monthly fuel prices were also tested, including averaging over a period of 1 – 6 months. As expected, the coefficient on fuel price was affected by this exploratory analysis; however, the coefficients on fuel price were non-significant under these tests and coefficients on other independent variables, including the coefficients on regulations, were not significantly changed when examining aggregated fuel prices.

4.2.2 Class 7 Trucks

Table 13 shows OLS regression coefficients for iterative model specifications for class 7 trucks. The results of regressions 1-4 show that Class 7 purchasing decisions are positive, elastic, robust and significant with respect to GDP. In fact, the general pattern is similar, with only GDP showing as a significant explanatory variable at the 5% level. From regression 1, we see that a 1% increase in GDP corresponds to a 6.90% increase in Class 7 truck sales. As with class 8 trucks, model 2 also shows the best fit of the models tested based on the adjusted R^2 value.

Table 13: Iterative model specifications for class 7 trucks

	(1)	(2)	(3)	(4)
GDP	6.940**	7.179**	7.732**	7.804**
Brent Oil		-0.108	-0.105	-0.106
Total Imports and Exports			-0.276	-0.272
Consumer sentiment				--0.028
Adj. R^2	0.412	0.414	0.413	0.411

*** p < 0.01; ** p < 0.05; * p < 0.1

4.3 Leading and Lagging Indicators

We iteratively tested for leading and lagging indicators. This exploratory analysis showed that GDP is a statistically significant leading indicator by 1-5 months. F-tests on the significance of the coefficient under the null hypothesis H_0: $\Delta \log GDP_t = 0$ showed that the null could be rejected ($p<0.1$) in tests up to t-5 months leading the regulation with the greatest significance seen in the F-test leading regulation by 1 month (Figure 13). Purchasing cycles described by industry suggest time between order and purchase is typically around 2 months and may vary by as much as 1 to 6 months from order to delivery. We include GDP leading by 2 months, which is aligned with theory based on industry insights and produced robust and significant estimators. Other variables tested did not show any increase in statistical significance when tested as leading or lagging variables.

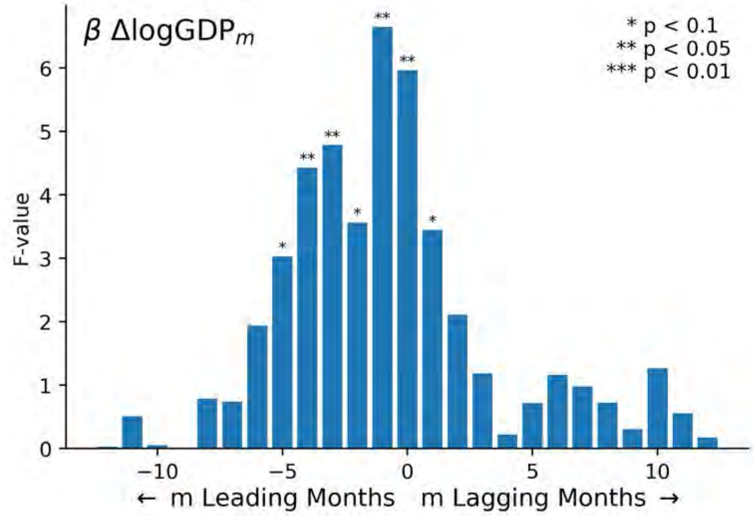

Figure 13: Testing the significance of the coefficient on β Δlog GDP under various lead/lag scenarios

4.4 Controlling for Regulations

Based on the previous exploratory analysis, we suggest the following model as best describing heavy-duty vehicle purchasing decisions.

Equation 4

$$\Delta logSales_{i,t} = \alpha + \beta_{1,t}Month_t + \beta_{j,t}\Delta logX_t + \beta_4 \mathrm{Pre}_{t-m} + \beta_5 \mathrm{Post}_{t+m} + \varepsilon_t$$

Where t represents the months elapsed since the start of the data, $Month_t$ controls for the month of year seasonality effects, and pre and post are binary variables where m represents the period of combined months *Pre* or *Post* regulation. β_1 controls for seasonality. X_t represents a vector of independent variables, including GDP, Brent Oil price, total imports and exports, and consumer sentiment, further discussed in Section 4.2. Given that unit roots are statistically identified in the data (discussed in Section 3.2), we find that taking the difference in the logs of the time series variables makes the data stationary. GDP in included in the vector X as a leading variable, as testing showed that leading GDP by 2 months increases the significance of the coefficient and is consistent with industry reported waiting times between date of order and date of delivery.

The coefficients on β_4 and β_5 estimate the effect of the "treatment" against the control. In this analysis the control group is the set of observations that occur outside of the pre- and post-regulatory periods, and the treatments are the periods pre- and post-regulation. Pre_{t-m} and $Post_{t+m}$ are binary variables that are equal to 1 during the period of analysis m months pre- or post-regulation, respectively, and are zero at all other times. The assumption in specifying β_4 and β_5 as such is that the factors that may lead to changes in these coefficients are solely due to the new standards, and are uncorrelated with other confounding factors, including seasonality, which is otherwise controlled for. As such, β_4 and β_5 capture the effect of the pre- or post-regulatory period relative to the control. If β_4 is positive and significant, then pre-buy behavior is indicated. Similarly, if β_5 is negative and significant, then low-buy behavior is indicated. [12]

4.4.1 Controlling for All Regulatory Periods Combined

As discussed in Section 3.3 we begin by combining all pre- and post- regulatory periods for different years into one explanatory variable, i.e. pre-2004, pre-2007, pre-2010, and pre-2014 were combined into a single variable in this model form, simply pre- and post-. This specification is aligned with form 2, described in Section 3.3. Analysis found that the most robust model specification was to combine months, therefore the pre- and post-regulation coefficients subsequently discussed should be interpreted as describing the change in HDV sales over the combined period of months from the date of regulation to the specified month (inclusive) pre- and post-regulation.

For three of the regulations in this analysis (2007, 2010, 2014), the date of regulation is January 1st. As such, we treat the December immediately prior to the regulation as month one pre-regulation. Similarly, we treat the remainder of the month of January following regulation as month one post-regulation. For the 2004 regulations, which went into effect on October 1st, 2002, we treat September 2002 as month one prior to regulation, and the remainder of the month of October 2002 as month one post-regulation.

These model results show evidence of pre-buy and low-buy in Class 8 sales pre- and post-regulation, respectively (Figure 14). Pre-buy coefficients generally did not show any consistent significance, while low-buy coefficients were significant in months 2-8 ($p < 0.05$) when considering all regulations together. Figure 14 through Figure 23 show the coefficients on the binary variables capturing the effect of regulation in the combined m months prior to the regulation going into effect. Positive

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[12] For the assumptions not to hold, effects would need to occur in conjunction with the regulations, and be uncorrelated with GDP, Brent oil price, imports and exports, consumer sentiment and seasonal factors. The coefficients on regulation would be biased if variables that covary with those regulatory indicators are omitted. We test for robustness and sensitivity of these results using a range of model specifications, leading and lagging periods, and varying periods of regulatory effects.

bars indicate an increase in vehicle purchases, while negative bars indicate a decrease in vehicle purchases during pre- and post-regulatory periods, all else equal.

These results show that, considering all regulations together, there is evidence of Class 8 pre-buy and low-buy activity. However, each regulation is different and so we present a similar analysis, by regulation, in Section 4.4.2 for Class 8 and Section 4.4.3 for Class 7.

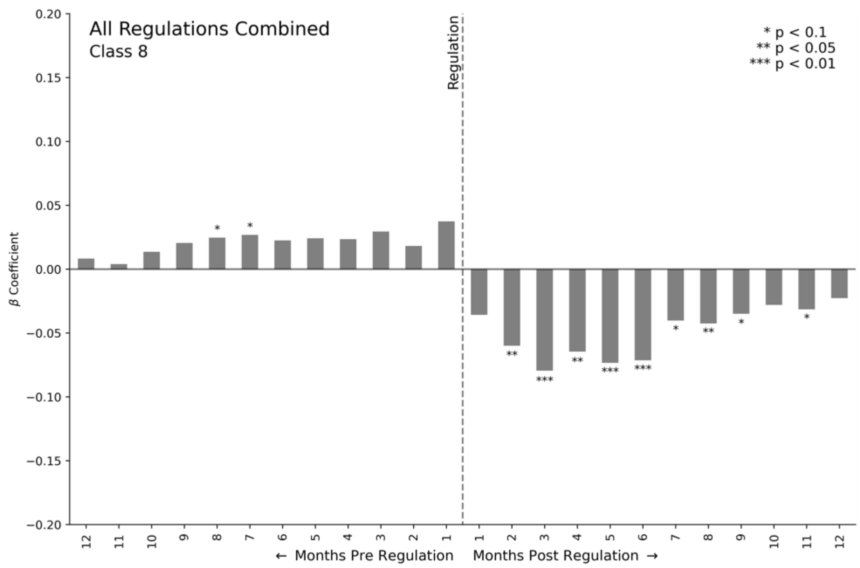

Figure 14: Coefficients grouped by months pre and post for all regulations combined (Class 8)

Model results for Class 7 show evidence that runs opposite, in terms of the pattern of coefficients, to the patterns seen in Class 8 sales, i.e. low-buy occurs prior to regulation, however, none of the coefficients for the combined regulatory periods were significant for Class 7 sales.

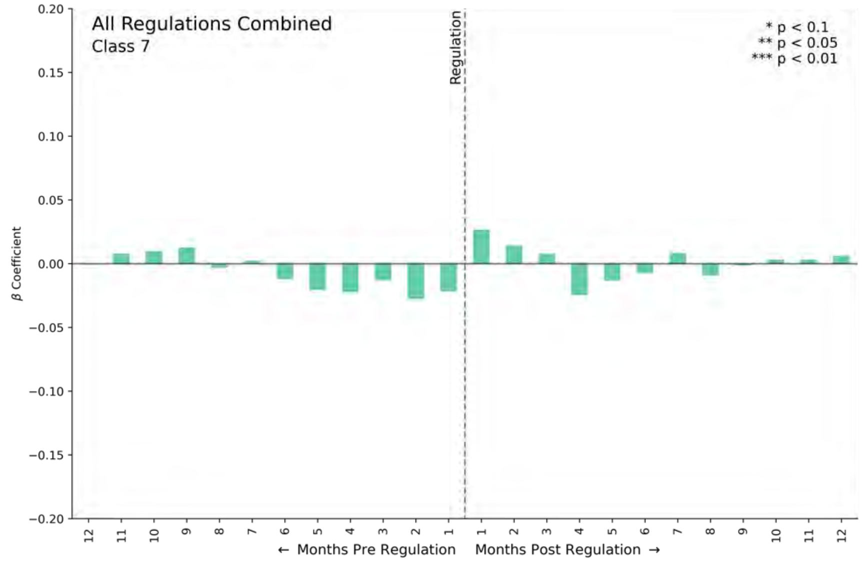

Figure 15: Coefficients grouped by months pre and post for all regulations combined (Class 7)

4.4.2 Class 8 Trucks

Figures for the individual regulations, where we vary the period m pre- and post-regulation, are shown graphically below in Figure 16 through Figure 19. Coefficients for other explanatory variables are robust to model specification, as seen in discussion of Table 12 and are therefore omitted here for brevity in favor of discussion of pre- and post- coefficients. Table 14 shows complete regression model results for five different model specifications. Each of the regulations is tested independently in models 1-4 (2004, 2007, 2010, and 2014 regulations, respectively), and model 5 shows all regulations tested together in the same model. Models 1-5 in Table 14 present results for the most significant months identified (or when not significant for the largest coefficients) for each regulation. Figure 16 through Figure 19 show the coefficients on the months pre- and post-regulation in order to demonstrate patterns in the pre-buy and low-buy behaviors.

Tables of the mean pre- and post-regulation coefficients are available in Section 4.6. Figure 16 shows coefficients from months pre/post 2004 where there is a pattern of pre-buy and low-buy. Looking at the p-values, no pre-buy effects are significant, while low-buy effects are only significant for the combined period up to 6 months post-regulation (β = -0.076, p < 0.1).

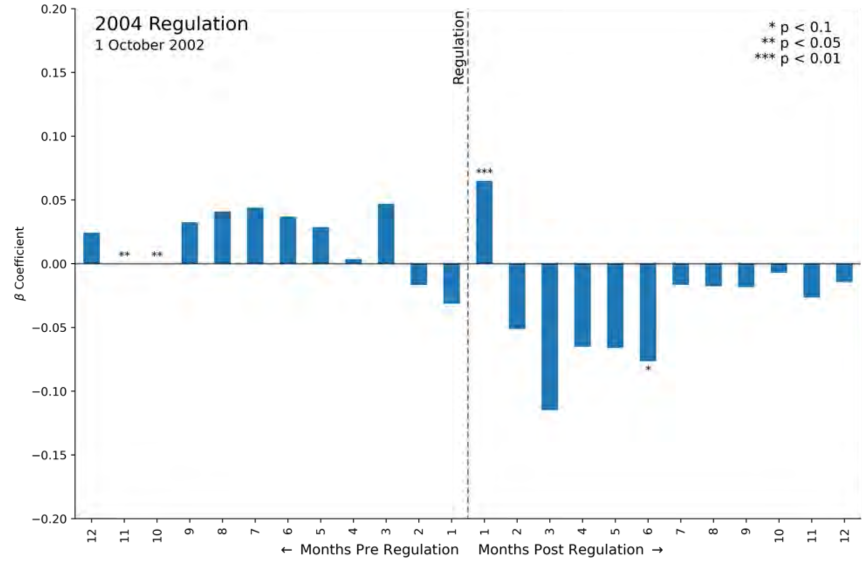

Figure 16: Coefficients grouped by months pre and post 2004 regulation (Class 8)

As discussed in Section 3.5, the coefficients on the regulations should be interpreted as percent changes in sales, i.e., the influence of the regulation over the period m months pre or post-regulation leads to an x % change in HDV sales. The coefficient for the combined three months post-2004 regulations is -0.076, indicating that the monthly percent change in Class 8 sales decreased during that time period by 7.6%. As shown in Figure 16, the low-buy effect diminished after month 6 post-regulation, losing statistical power and converging on zero after around 7 months. The observed increase in sales one month post-regulation may be a result of the regulations being brought forward to October 2002, reflecting delivery of pre-existing orders.

The data around the 2007 regulations (Figure 17) demonstrate clear evidence of low buy effects, with little support for pre-buy around that regulation. All months post-2007 regulations show negative and significant values ($p < 0.01$ for months 1-9, $p < 0.05$ for all other months), thus strongly supporting evidence for low-buy effects. The strongest and most significant effects were seen in the periods 1 - 4 months post- (β = -0.143, $p < 0.01$), 1-5 months post- (β = -0.144 $p < 0.01$), and 1-6 months post-regulation (β = -0.149, $p < 0.01$). These data indicate that over the combined 6-month period post 2007 regulations going into effect, all else equal, the percent change in Class 8 vehicle sales decreased by 14.9%. As shown in Figure 17 the low-buy effect post-2007 remains significant at $p < 0.01$ out to 9 months post-regulation but was greatest around 6 months post-regulation decreasing thereafter. As with the 2004 regulations, this evidence indicates that low-buy effects may be short-lived.

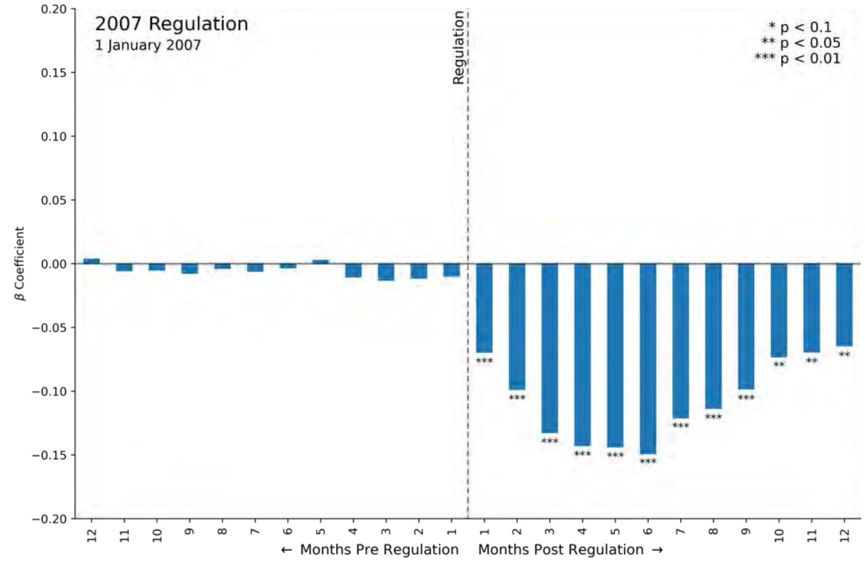

Figure 17: Coefficients grouped by months pre and post 2007 regulation (Class 8)

Data from the Federal Reserve show that the Great Recession began around Q1 of 2008. We do not anticipate that the effects observed for the 2007 low-buy are affected by the Great Recession. First, by including $\Delta log\ GDP$ as an independent variable, the model controls for changes in GDP, which are used as indicators for a range of macroeconomic conditions. Changes in GDP are highly correlated with recession periods. As such, the model effectively controls for recession periods. Second, the time period analyzed for the 2007 low-buy predates the start of the recession period, and in fact shows a diminishing effect after 6 months post-regulation. The recession period began approximately 13 months post the 2007 regulation going into effect. If the recession were impacting low-buy then the observed reduction in low-buy coefficients, and corresponding reduction in significance, would not be expected approaching the recession period.

Evidence from the OLS models suggests pre-buy associated with the 2010 regulations. This effect was strongest in months 1 ($\beta = 0.078$), and combined months 1- 2 ($\beta = 0.105$) and 1-4 ($\beta = 0.079$) months pre-regulation but is statistically significant ($p < 0.05$) over the combined 8 months prior to the regulation ($\beta = 0.057$, $p < 0.05$). Low-buy effects are generally strongest and most significant in months 1 ($\beta = -0.144$, $p < 0.01$) and months 1-2 ($\beta = -0.083$, $p < 0.1$) with evidence supporting a switch from pre-buy to low-buy preferences around the regulation, though the period of statistical significance is shorter (2 months) for low-buy than for the pre-buy. Looking at the coefficients for 2 months pre- and post-regulation, we see that the pre-buy ($\beta = 0.105$) and low-buy ($\beta = -0.083$)

effects do partially cancel one another out, though the pre-buy period of significance is longer and larger than for the low buy.

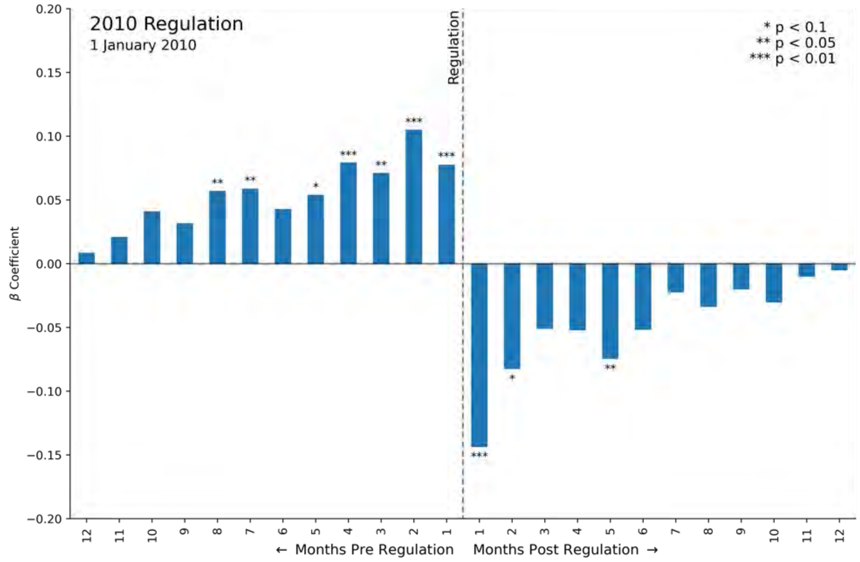

Figure 18: Coefficients grouped by months pre and post 2010 regulation (Class 8)

The 2014 regulations (Figure 19) only show statistical significance for pre-buy evidence in the one month prior to the regulation ($\beta = 0.133$, $p < 0.01$), with no support for low-buy following the regulations going into effect. This pre-buy effect is short-lived and may be a result of last-minute vehicle deliveries in the month prior to the regulation going into effect. The short-lived nature of the pre-buy effect is intuitive as the 2014 Phase I regulations increased capital costs, but also offered improved fuel economy, thereby reducing overall operating costs. Given the short-term nature of this effect, it is possible that technological uncertainty around the regulation is driving this short-term pre-buy behavior.

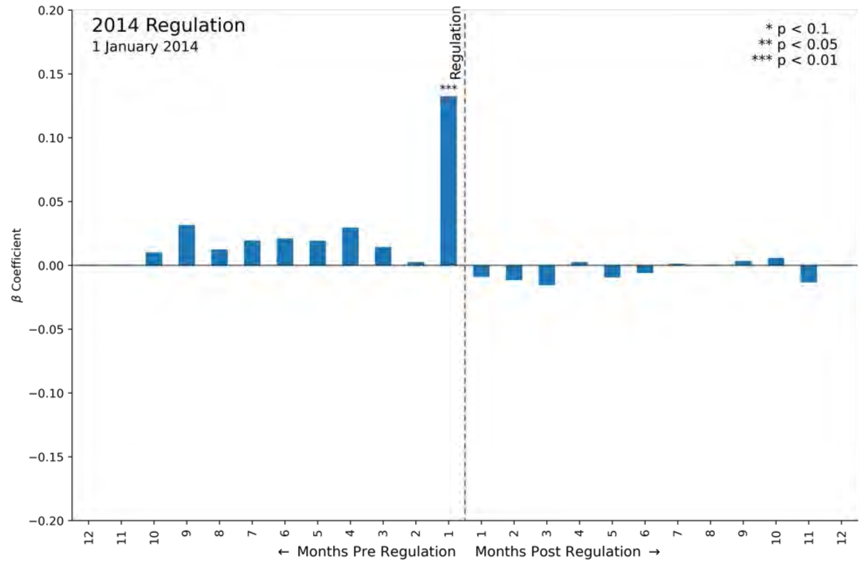

Figure 19: Coefficients grouped by months pre and post 2014 regulation (Class 8)

Table 14: Class 8 regression model summary. Standard errors are shown in parentheses.

	Model				
Variable	1	2	3	4	5
Intercept	-0.327***	-0.323***	-0.328***	-0.331***	-0.313***
	(0.022)	(0.021)	(0.02)	(0.021)	(0.021)
February	0.335***	0.335***	0.336***	0.335***	0.334***
	(0.028)	(0.026)	(0.027)	(0.027)	(0.027)
March	0.502***	0.502***	0.503***	0.502***	0.501***
	(0.031)	(0.029)	(0.031)	(0.031)	(0.03)
April	0.296***	0.299***	0.299***	0.299***	0.294***
	(0.036)	(0.035)	(0.035)	(0.036)	(0.034)
May	0.343***	0.347***	0.343***	0.347***	0.339***
	(0.027)	(0.025)	(0.024)	(0.026)	(0.025)
June	0.355***	0.359***	0.351***	0.359***	0.346***
	(0.028)	(0.026)	(0.026)	(0.028)	(0.026)
July	0.243***	0.238***	0.240***	0.246***	0.225***
	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)
August	0.338***	0.333***	0.334***	0.341***	0.320***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.03)
September	0.298***	0.294***	0.294***	0.301***	0.281***
	(0.028)	(0.027)	(0.026)	(0.027)	(0.028)
October	0.372***	0.364***	0.366***	0.372***	0.355***

	(0.028)	(0.027)	(0.026)	(0.027)	(0.028)
November	0.214***	0.207***	0.206***	0.213***	0.198***
	(0.03)	(0.031)	(0.03)	(0.031)	(0.031)
December	0.498***	0.491***	0.490***	0.491***	0.476***
	(0.027)	(0.028)	(0.027)	(0.027)	(0.026)
GDP	7.432**	7.066**	8.107**	7.407**	7.294**
	(3.464)	(3.504)	(3.484)	(3.572)	(3.488)
Brent Oil Price	-0.11	-0.113	-0.137	-0.12	-0.132
	(0.085)	(0.087)	(0.086)	(0.087)	(0.084)
Total Imports and Exports	0.434	0.526	0.4	0.477	0.478
	(0.648)	(0.641)	(0.664)	(0.627)	(0.686)
Consumer Sentiment	0.019	0.015	0.024	0.019	-0.027
	(0.132)	(0.129)	(0.129)	(0.132)	(0.126)
Pre_2 2004	-0.018				-0.014
	(0.017)				(0.017)
$Post_6$ 2004	-0.072				-0.076*
	(0.047)				(0.044)
Pre_2 2007		-0.015			-0.013
		(0.018)			(0.016)
$Post_6$ 2007		-0.145***			-0.151***
		(0.02)			(0.019)
Pre_8 2010			0.056**		0.053**
			(0.025)		(0.025)
$Post_5$ 2010			-0.064**		-0.076**
			(0.031)		(0.031)
Pre_1 2014				0.127***	0.129***
				(0.021)	(0.018)
$Post_2$ 2014				-0.001	-0.018
				(0.016)	(0.016)
Observations	228	228	228	228	228
R^2	0.683	0.699	0.685	0.68	0.717
Adjusted R^2	0.657	0.675	0.66	0.654	0.685

***p<0.1; **p<0.05; ***p<0.01**

4.4.3 Class 7 Trucks

Figures for the individual regulations for Class 7 vehicles are shown graphically below in Figure 20 through Figure 23. As with Class 8 trucks, the other explanatory variables are robust to model specification, thus this analysis focuses on the coefficients on pre-buy and low-buy. Table 15 shows complete regression model results for five different model specifications. Each of the regulations is tested independently in models 1-4 (2004, 2007, 2010, and 2014 regulations, respectively), and model 5 shows all regulations tested together in the same model. Models 1-5 in Table 15 present results for the most significant months identified (or when not significant for the largest coefficients) for each regulation. Figure 20 through Figure 23 show the coefficients on the months pre- and post-regulation in order to demonstrate patterns in the pre-buy and low-buy behaviors.

Figure 20 shows coefficients from combined months pre/post 2004 where the pre-buy and low-buy behavior is apparently reversed, with low-buy occurring prior to the regulation, and increased deliveries post-regulation. Low-buy effects are significant through the period five months pre-regulation combined ($p < 0.05$), while increased purchases are only generally significant in month 2 ($p < 0.05$) post-regulation.

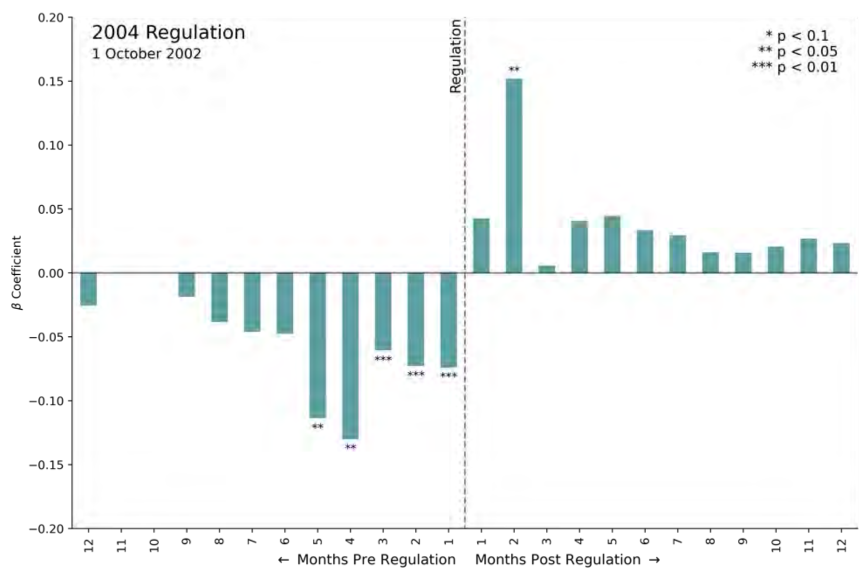

Figure 20: Coefficients grouped by months pre and post 2004 regulation (Class 7)

The data around the 2007 regulations (Figure 21) show non-significant evidence for both pre-buy and low-buy effects. While graphically the coefficients are generally less than zero post-regulation, these values are not significantly different from zero.

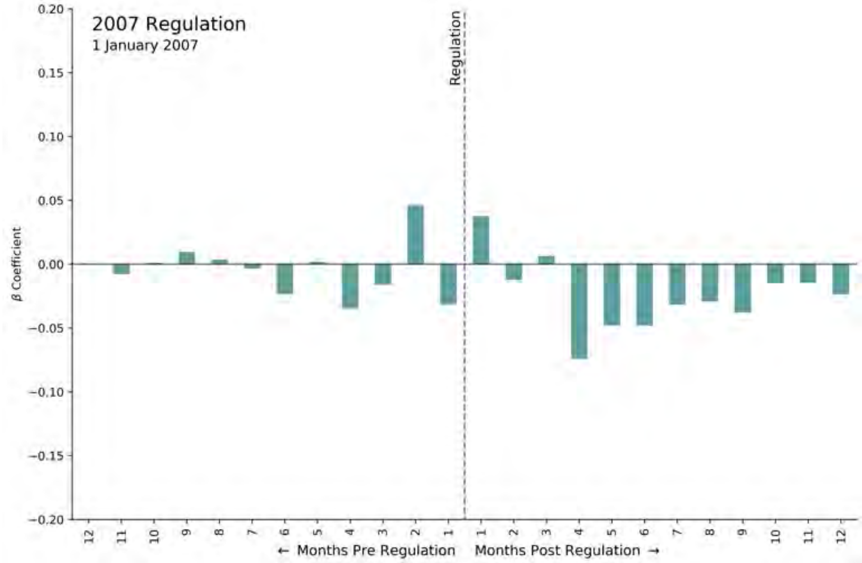

Figure 21: Coefficients grouped by months pre and post 2007 regulation (Class 7)

Evidence from the OLS models suggests low-buy of Class 7 vehicles prior to the 2010 regulations (Figure 22). This effect was strongest in the one month pre-regulation ($\beta = -0.069$, $p < 0.1$), with no other months showing significance. There was no significant evidence for low buy post 2010 regulations for class 7 vehicles. Taken together with evidence of a shift in the ratio of Class 8 to Class 7 deliveries ahead of the 2010 regulations, one reasonable explanation for this is substitution from Class 7 to Class 8, i.e. class shifting, ahead of the regulations. See Section 4.5 for further discussion.

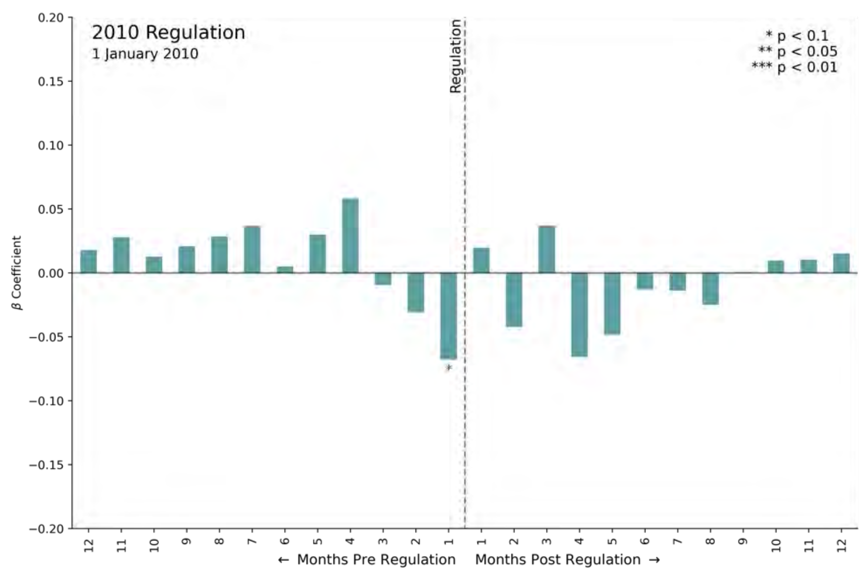

Figure 22: Coefficients grouped by months pre and post 2010 regulation (Class 7)

The 2014 regulations (Figure 23) only show significant pre-buy evidence in the one month prior to the regulation ($\beta = 0.082$, $p < 0.05$), with no statistical support for low-buy following the regulations going into effect.

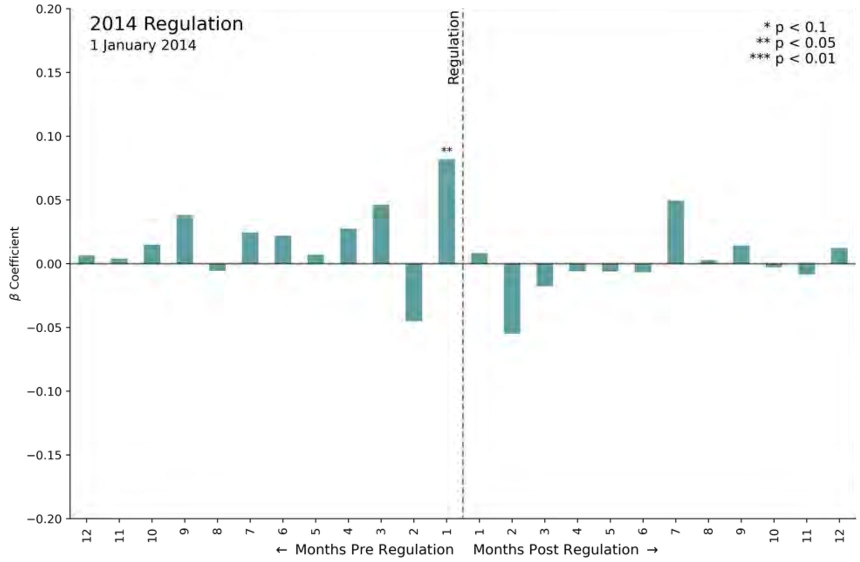

Figure 23: Coefficients grouped by months pre and post 2014 regulation (Class 7)

Table 15: Class 7 regression model summary (standard errors are shown in parentheses)

	Model				
Variable	1	2	3	4	5
Intercept	-0.097***	-0.093***	-0.095***	-0.094***	-0.086***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.025)
February	0.065**	0.066**	0.066**	0.065**	0.066**
	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)
March	0.247***	0.248***	0.248***	0.244***	0.245***
	(0.03)	(0.03)	(0.031)	(0.03)	(0.032)
April	0.036	0.036	0.036	0.033	0.032
	(0.044)	(0.044)	(0.044)	(0.045)	(0.043)
May	0.079**	0.071**	0.071**	0.071**	0.070*
	(0.034)	(0.035)	(0.035)	(0.034)	(0.036)
June	0.142***	0.133***	0.134***	0.134***	0.133***
	(0.036)	(0.039)	(0.039)	(0.039)	(0.037)
July	0.081**	0.072*	0.072*	0.073*	0.070*
	(0.039)	(0.039)	(0.039)	(0.039)	(0.041)
August	0.147***	0.138***	0.138***	0.138***	0.137***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.04)

September	-0.038	-0.047	-0.047	-0.047	-0.048
	(0.036)	(0.037)	(0.037)	(0.036)	(0.038)
October	0.182***	0.186***	0.186***	0.186***	0.170***
	(0.036)	(0.036)	(0.036)	(0.035)	(0.038)
November	-0.116***	-0.115***	-0.112***	-0.111***	-0.129***
	(0.036)	(0.038)	(0.038)	(0.038)	(0.038)
December	0.189***	0.183***	0.190***	0.182***	0.175***
	(0.035)	(0.036)	(0.037)	(0.036)	(0.039)
GDP	8.361*	7.896	8.301*	7.84	7.593
	(4.883)	(4.932)	(4.934)	(4.996)	(5)
Brent Oil Price	-0.128	-0.141	-0.137	-0.14	-0.135
	(0.1)	(0.101)	(0.1)	(0.101)	(0.101)
Total Imports and Exports	-0.738	-0.719	-0.685	-0.732	-0.583
	(0.768)	(0.768)	(0.732)	(0.765)	(0.746)
Consumer Sentiment	-0.028	-0.021	-0.016	-0.033	-0.032
	(0.156)	(0.158)	(0.158)	(0.158)	(0.157)
Pre_5 2004	-0.114**				-0.114**
	(0.049)				(0.049)
$Post_2$ 2004	0.148**				0.149**
	(0.075)				(0.076)
Pre_2 2007		0.05			0.054
		(0.058)			(0.06)
$Post_4$ 2007		-0.07			-0.076
		(0.065)			(0.065)
Pre_1 2010			-0.072**		-0.061*
			(0.03)		(0.033)
$Post_4$ 2010			(0.061)		-0.068
			(0.094)		(0.095)
Pre_1 2014				0.089***	0.089***
				(0.03)	(0.033)
$Post_2$ 2014				-0.053	-0.061
				(0.042)	(0.043)
Observations	228	228	228	228	228
R^2	0.426	0.412	0.411	0.41	0.437
Adjusted R^2	0.380	0.364	0.363	0.362	0.373

***p<0.1; **p<0.05; ***p<0.01**

4.5 Exploring the Potential for Class Shifting

To explore the potential for class shifting, we regress the ratio of Class 8 to Class 7 trucks against the dependent variables GDP and Brent Oil price, controlling for seasonality. The ratio of Class 8 to Class 7 sales, shown in Figure 24, is not constant over the time period studied, varying from between 1.031 in March of 2001 and 1.214 in December of 2011.

Figure 24: Class 7 and 8 monthly sales (top), ratio of the logs (middle) and first difference in the ratio of the logs (bottom) of Class 8 to Class 7 vehicle sales

While Figure 24 shows that Class 8 sales show more variation than Class 7 sales, both series do show variation over the time period studied (Class 7 mean = 5,422, std dev = 1,929; Class 8 mean = 15,444, std dev = 4,817). The Class 8 and Class 7 time series are weakly correlated (Pearson's r = 0.44), and the difference in the logs is slightly more positively correlated (Pearson's r = 0.539) though the relationship is not a strong correlation. As shown in Figure 24, taking the difference in the logs of the two sales time series data makes the data stationary, which was confirmed using a KPSS test ($\frac{log\ Sales_{Class8}}{log\ CSales_{Class7}}$ KPSS p-value > 0.1, $\Delta\frac{log\ Sales_{Class8}}{log\ Sales_{Class7}}$ KPSS p-value = 0.027).

The functional form of the class shifting regression is shown in Equation 5, where Y_m represents the set of coefficients on m months pre- and post- regulation, allowing us to test for the influence of regulation on the ratio of Class 8 to Class 7 sales as a function of total Class 7 and 8 sales.

Equation 5

$$\Delta \frac{log\ Sales_{Class8}}{log\ Sales_{Class7}} = \alpha + \beta_1 Month + \beta_2 \Delta logX\ + \beta_j Y_m$$

The results of the class shifting regressions show that month of year ($p < 0.01$ for all months) remains significant, along with imports + exports ($p < 0.05$). GDP ($p > 0.1$), Brent Oil price ($p > 0.1$) and Consumer sentiment are not significant factors affecting the ratio of Class 8 to Class 7 sales (Table 16). Table 16 is shown below as an example of the coefficients for each regulation for the periods 2 months pre and post-regulation. As with the other model specifications, the independent variables not controlling for regulation are robust to model specification, regardless of the length of pre- or post-regulatory period modeled.

Table 16: Coefficients for the ratio of Class 8 to Class 7 monthly sales for the 2 month period pre- and post-regulation

	β
GDP	-0.3677
Brent Oil	-0.0002
Total Imports and Exports	0.1811**
Consumer sentiment	0.0048
Pre_2 2004	0.0079***
$Post_2$ 2004	-0.0258
Pre_2 2007	-0.0072
$Post_2$ 2007	-0.0098***
Pre_2 2010	0.0178***
$Post_2$ 2010	-0.0052
Pre_2 2014	0.007**
$Post_2$ 2014	0.0061
Adj. R^2	0.263

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Figure 25 through Figure 28 show the mean regression coefficients for the 2004, 2007, 2010, and 2014 regulations, respectively.

It is important to consider that, given data availability and restrictions, the results described in this section are best thought of as indicators for possible class shifting. There are a few ways in which the ratio of Class 8 to Class 7 HDV sales may increase. For example, Class 8 sales may increase while Class 7 sales remain unchanged or decrease, Class 8 sales remain unchanged and Class 7 sales decline, or both Class 8 and Class 7 sales change in a way that results in a relative increase in the ratio. None of these scenarios necessarily requires a shift in sales from one class to another but may be indicative of the right conditions for potential class shifting. Class shifting, if it occurs, is likely to occur at the margin as regulatory constraints occur, and thus large changes are not anticipated.

Figure 25 shows that the ratio of Class 8 sales relative to Class 7 increased significantly during the 7-month period preceding the 2004 regulations going into effect (on 1 October 2002) ($p < 0.05$ in all months except 5 and 7 months prior where $p < 0.1$). Conversely, post-regulation, the regression coefficients show a decrease in the ratio, i.e. an increase in Class 7 purchases relative to Class 8, though the coefficients are non-significant, with the exception of the period 5 months combined post regulation. These coefficients indicate an increase in preference for Class 8 vehicles over Class 7 vehicle in the months prior to the 2004 regulations going into effect. As discussed in Section 4.4.2, the observed pre-buy effects for Class 8 vehicles were weak and non-significant. The data do not show a significant increase in Class 8 purchases but do show a small statistically significant ($\beta = 0.017$, $p < 0.01$) preference for Class 8 vehicles relative to Class 7, coupled with decreased Class 7 sales prior to the regulation (Figure 20). All else equal, these results are indicative of possible class shifting from Class 7 to Class 8 ahead of the 2004 regulations going into effect.

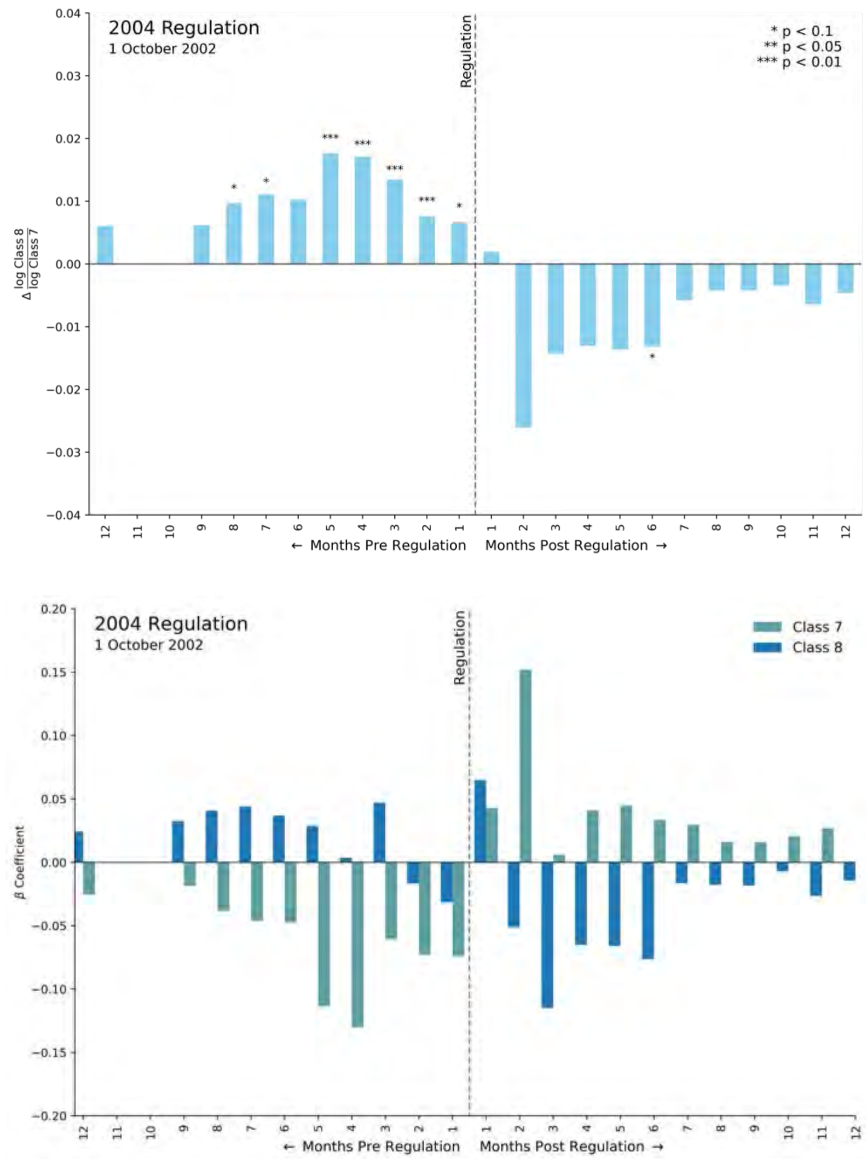

Figure 25: Coefficients grouped by months pre and post 2004 regulation on the ratio of Class 8 to Class 7 vehicle sales (top) and the coefficients for Class 8 and Class 7 sales (bottom) as discussed in Section 4.4

Figure 26 shows the pre- and post- regulation coefficients for the 2007 NOx regulations. Unlike the 2004 regulations, the ratio of Class 8 to Class 7 sales does not increase prior to the regulation going into effect. Post-regulation the data show a significant reduction ($p < 0.05$) in the ratio of Class 8 to Class 7 sales over the period eight months post-regulation, except for months 4 and 5 post-regulation. Given the data show statistically significant evidence of Class 8 low-buy effects (Figure 17) post-regulation, with no observed statistical change in Class 7 sales (Figure 21), it is difficult to draw inference of class shifting from this reduction in the ratio of Class 8 to Class 7 vehicles as it is challenging to tell whether the reduction in the ratio is driven by low buy of Class 8 vehicles or class shifting.

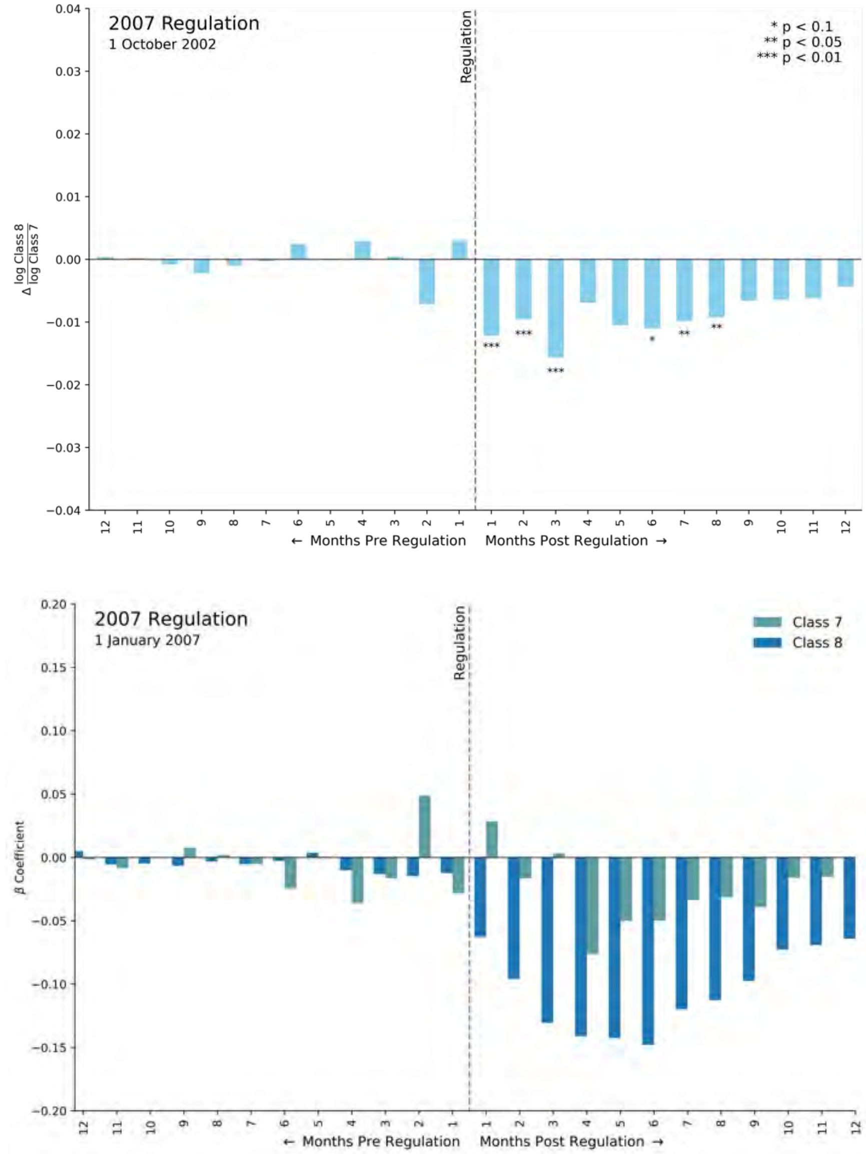

Figure 26: Coefficients grouped by months pre and post 2007 regulation on the ratio of Class 8 to Class 7 vehicle sales (top) and the coefficients for Class 8 and Class 7 sales (bottom) as discussed in Section 4.4

The data from 2010 show a statistically significant ($p < 0.01$) increase in the ratio of Class 8 to Class 7 vehicle sales in the three months prior to the regulation (Figure 27), and a statistically significant decrease ($p < 0.01$) in the ratio in the month following regulation. This pattern is similar to the pre-buy and low-buy pattern observed in Class 8 sales (Figure 18). Given evidence of short-run low-buy in Class 7 vehicle sales (Figure 22), all else equal, these results are indicative of possible class shifting from Class 7 to Class 8 ahead of the 2010 regulations.

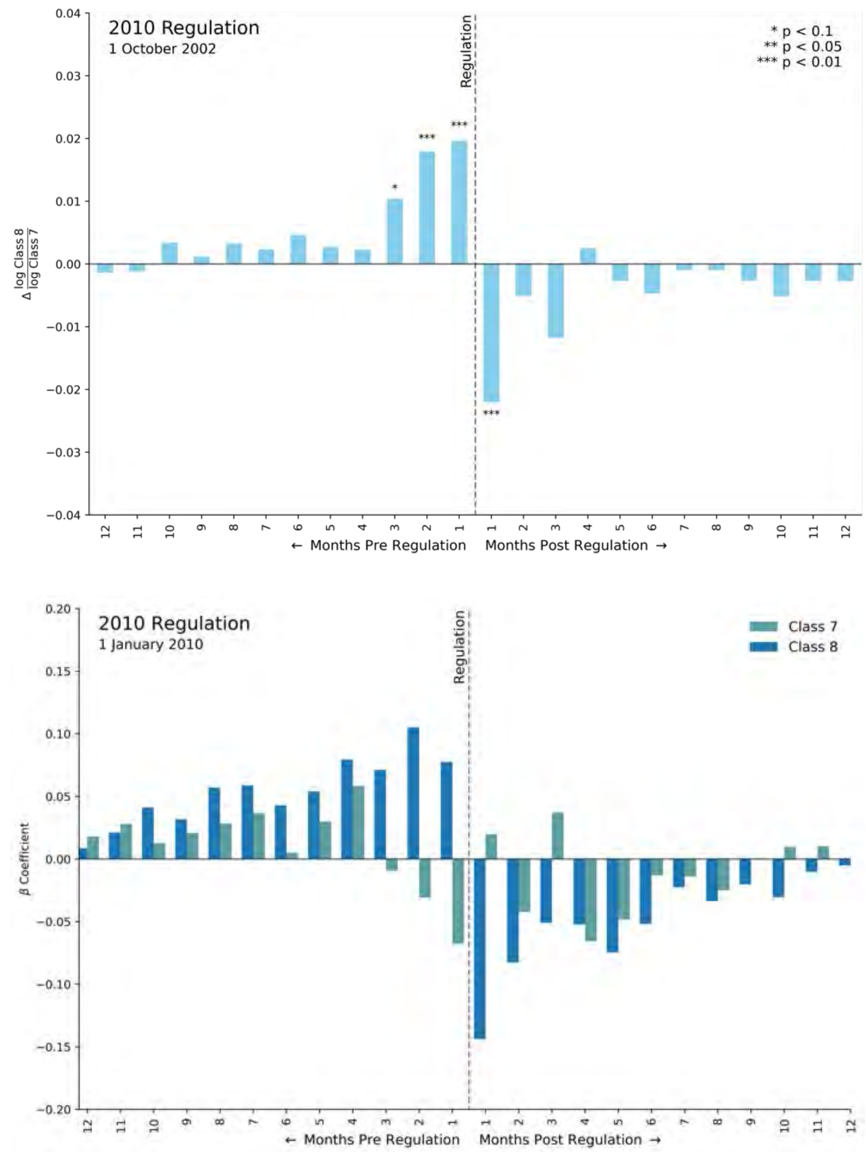

Figure 27: Coefficients grouped by months pre and post 2010 regulation on the ratio of Class 8 to Class 7 vehicle sales

Figure 28 shows the coefficients on months before and after the 2014 regulations. The coefficients do not show a discernible pattern regarding preferences for Class 8 vehicles relative to Class 7 vehicles around the regulation. Two months prior to the regulation the coefficients are positive and weakly significant ($p < 0.1$), though the magnitude of the coefficient is small indicating minimal evidence for possible class shifting occurring around the 2014 regulations.

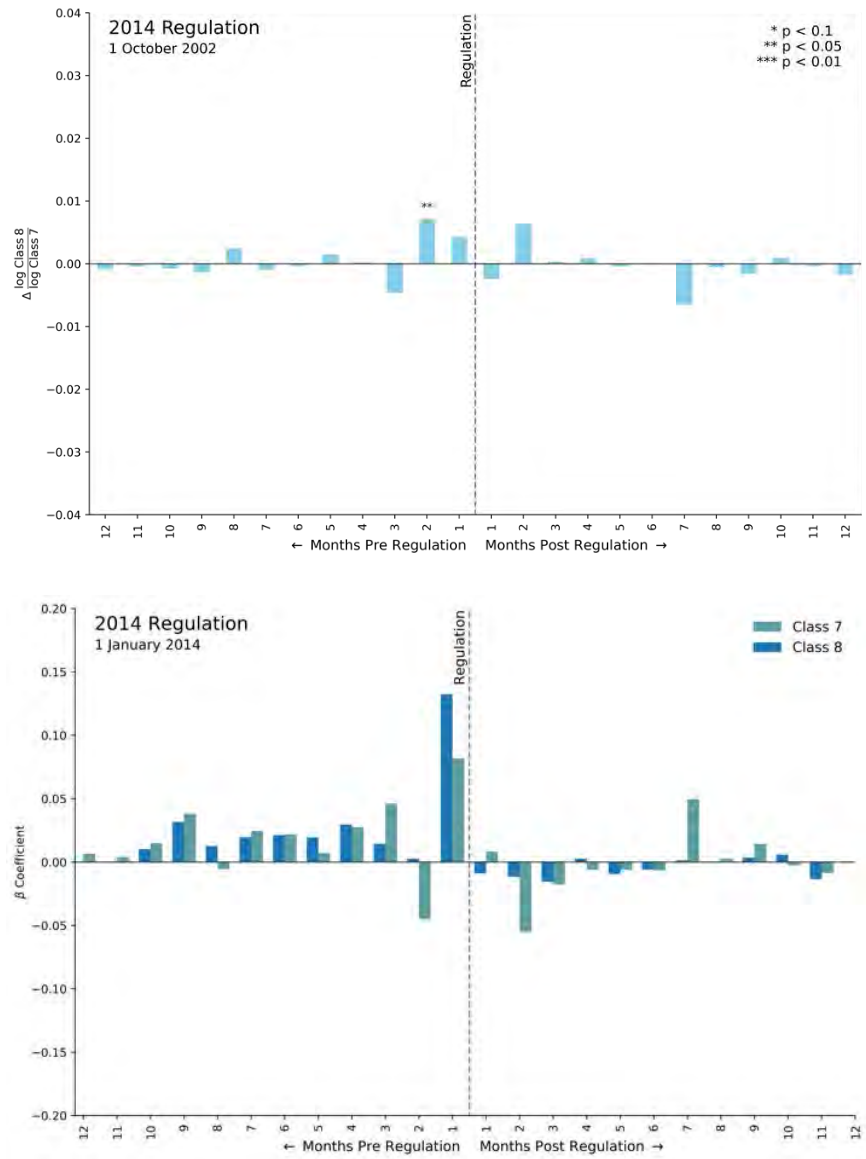

Figure 28: Coefficients grouped by months pre and post 2014 regulation on the ratio of Class 8 to Class 7 vehicle sales

This exploratory analysis of the potential for class-shifting suggest the potential for class shifting associated with the 2004 and 2010 regulations. These results, and the literature in the area, indicate that the subject of class-shifting may merit further study, with these observations and the methods presented here offering a potential avenue for further study. This work may be complemented by further studies of class switching including those using microeconomic methods in parallel with the macroeconomic approaches demonstrated in this work.

4.6 The Effects of Pre-Buy and Low-Buy Behavior

Table 17 shows the mean coefficients and significance levels for the Class 8 pre- and post-regulation coefficients for each of the regulations studied, 2004, 2007, 2010, and 2014. These data are an alternative representation of the data in Figure 16 through Figure 19, and clearly show the periods of significance for each regulation in bold text.

The only regulations for which the pre-buy coefficients are significant are the 2010 regulation (8 months pre-regulation ($p < 0.05$)) and the 2014 regulation (1 month prior ($p < 0.01$)). We define the Temporally Adjusted Pre-buy Sales rate (TAPS) as the duration of the pre-buy effect multiplied by the scale of the effect. The maximum TAPS occurs prior to the 2010 regulations, corresponding to a 5.7% increase in vehicle sales over the 8 months of purchases preceding the regulation, corresponding to a value of 0.456. The minimum TAPS is zero, corresponding to both 2004 and 2007, where no pre-buy effect was observed.

We define the Temporally Adjusted Low-buy Sales rate (TALS) similarly to TAPS, as the duration of the low-buy effect multiplied by the scale of the effect. The minimum TALS is zero, corresponding to the 2014 regulations, and the maximum TALS is seen in the 8 months post-2007 regulations, corresponding to an 11.4% decrease over 8 months, for a TALS of -0.912.

The maximum TAPS and TALS values were both observed in the period 8 months pre or post-regulation. As such, these findings suggest that 8 months pre- and post-regulation is an appropriate period for analysis of maximum pre-buy and low-buy elasticities.

Table 17: Coefficients and significance for combined months pre- and post-regulation for the 2004, 2007, 2010, and 2014 regulations. Significant coefficients shown in bold

		2004	2007	2010	2014
Combined Months Pre-Regulation	12	0.024	0.004	0.009	0.000
	11	**-0.0****	-0.006	0.021	0.000
	10	**0.0****	-0.005	0.041	0.010
	9	0.032	-0.008	0.032	0.032
	8	0.041	-0.004	**0.057****	0.013
	7	0.044	-0.006	**0.059****	0.019
	6	0.037	-0.004	0.043	0.021
	5	0.029	0.003	**0.054***	0.019
	4	0.004	-0.011	**0.079*****	0.030
	3	0.047	-0.013	**0.071****	0.014
	2	-0.017	-0.012	**0.105*****	0.003
	1	-0.032	-0.01	**0.078*****	**0.132*****
Combined Months Post-Regulation	1	**0.065*****	**-0.07*****	**-0.144*****	-0.009
	2	-0.051	**-0.099*****	**-0.083***	-0.012
	3	-0.115	**-0.133*****	-0.051	-0.015
	4	-0.065	**-0.143*****	-0.052	0.003
	5	-0.066	**-0.144*****	**-0.075****	-0.009
	6	**-0.076***	**-0.149*****	-0.052	-0.006
	7	-0.017	**-0.121*****	-0.022	0.001
	8	-0.018	**-0.114*****	-0.034	0.000
	9	-0.018	**-0.099*****	-0.020	0.003
	10	-0.007	**-0.073****	-0.030	0.006
	11	-0.027	**-0.07****	-0.010	-0.013
	12	-0.014	**-0.065****	-0.005	0.000

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

TAPS and TALS capture the maximum observed pre-buy and low-buy effects across the four regulatory periods studied in this analysis. However, the two metrics will not have the same long-term impacts. TAPS effects are expected to be longer lived and persist over multiple years as the pre-regulatory truck is used during the post-regulatory period and enters the secondary or scrappage markets at the end of its useful life.

The effects of pre-buy may be thought of as follows. The No Action path in Figure 29 represents the pathway where no new vehicle is purchased, and vehicular emissions continue at rate E_0. The Regular Purchase path represents the pathway when the purchasing cycle is unchanged, and the new vehicle is purchased in the post-regulation environment (T_{pe}). The Pre-Buy Purchase path represents the case where the new vehicle, though cleaner than the existing vehicle, is purchased ahead of the new regulations at time T_p. T_R is the time of regulation.

The increased vehicles purchased in the pre-buy period can be assumed to be early replacements for what would have been a purchase in the post-regulatory environment. The pre-buy purchase will remain in the vehicle fleet for a significant period of time (e.g., lifetime of the vehicle), which we call T_{LT}, measured in years. During this period, the environmental benefits of the regulation, defined as the delta between the emissions of the pre-buy HDV (E_{pre}) and the emissions of the post-regulatory HDV (E_{post}) (area C), are not captured. If emissions are measured in g/bhp-hr and a truck uses P amount of bhp-hr per year of energy, this impact could be defined as: $[E_{pre} – E_{post}]$ x T_{LT} x P and would be equivalent to area A+B in Figure 29. For a fleet of N vehicles, the total emission impact is: $[E_{pre} – E_{post}]$ x T_{LT} x P x N.

However, the pre-buy vehicle may displace an older vehicle for the period of time equal to the time of purchase (T_p) and the time in which the user would have normally purchased a vehicle in a post-regulatory environment (T_{pe}).

This provides a short-run environmental benefit, equivalent to area A in Figure 29. After the point at which the purchase may normally occur, T_{pe}, emissions are beneficial compared to E_0 (area B), but not when compared to E_{post} (area B+C), if we assume the newer vehicle will be used in place of an older vehicle. It is clear from Figure 29 that this benefit (area B) is not equal to the full benefit of the new regulation (area B + C). We expect this "pre-buy benefit" (area A) to be non-zero, but modest since we anticipate that $[T_{pe} – T_p]$ would be relatively short-term and would not offset the longer-term benefits seen under the new regulations.

The emissions benefits of a purchase in a normal cycle are equal to area B + C. The emissions benefits in a pre-buy purchase are equal to area A + B. Therefore, the difference in emissions between the two purchasing pathways is equal to area C – A. As we anticipate that the time delta between T_p and T_{pe} is small (less than a year), area A goes to zero, and therefore the benefit of purchasing under a normal cycle compared to a pre-buy is equal to area C.

Figure 29: Diagram showing conceptual effects of pre-buy purchasing behavior

Conversely, TALS effects are short-lived, likely on the multi-month scale, rather than multiple years. The regulatory impacts resulting in TALS effects are more challenging to parse out, as there may be a set of impacts, that result in low-buy purchases. These impacts fall into three categories.

- First, pre-buy impacts may affect low-buy, as purchasing firms may have already purchased new vehicles in the pre-buy regime.
- Second, experiential delay may cause purchasing firms to delay their purchases until greater experience is achieved with regulatory-compliant vehicles. This effect may be particularly pronounced for regulations requiring technologies that are nascent to the industry or require substantial operational changes.
- Third, price delay effects may cause firms to delay their purchases since the price of regulatory-compliant vehicles is higher, and so it is more cost-effective to maintain and continue to use older vehicles.

The impact of pre-buy impacts on low-buy purchases would theoretically be captured in the pre-buy analysis. In the case that similar magnitudes of pre-buy and low-buy are observed we may assume that the low-buy is explained by the earlier increase in purchases pre-regulation. If, however, there is a remainder of low-buys then those effects may be attributable to the second and third effects described; experiential and price delay effects. Experiential and price delay effects are not likely to be a persistent problem, as those existing older vehicles will need to be replaced by new, regulatory-compliant vehicles, once they reach the end of their useful economic life, and any experiential issues have been resolved by manufacturers and trucking firms (National Academies of Sciences Engineering and Medicine 2020).

4.7 Exploring the Potential Effect of Anticipated Regulatory Cost on Purchasing Behavior

Anticipated regulatory costs are discussed in Section 2.8. As shown in Table 3, EPA estimated the 2004 regulations (implemented 1 October 2002) would increase the net present value of HDV diesel costs by $1,004 (2019$) and the 2007 regulations would increase total costs (capital plus operations and maintenance) by $10,811, and the 2010 regulations by $9,868.[13] This section presents exploratory analysis of the potential effect of anticipated regulatory costs on purchasing behaviors. A number of important caveats remain when considering this analysis, discussed in greater detail in Section 4.7.2. These include consideration that the estimated coefficients likely also capture unobserved aspects of the regulations, such as potential concerns over unintended side effects of the technologies used to meet the standards, including reliability and maintenance concerns. Additionally, demand elasticities are estimated using anticipated, not observed, prices. As such, anticipated or real prices of regulation may have differed from those estimated in the literature, with firms having better information on prices. Last, the time period of these coefficients should be considered, as the underlying coefficients indicate short time periods in which the effects occur.

Given the functional form used to estimate the regression models, the coefficients on regulations discussed in Section 4.4 can be used to calculate elasticities of demand for HDVs. It is useful to remember that the functional form of the regression models specified include a binary variable for a period of months pre- and post-regulation. As such, the information captured in the coefficient for this variable is not just limited to the price (capital and O+M) changes associated with regulation, but also other unobserved factors, such as vehicle reliability and control technology uncertainty. Recent prices for Class 8 trucks are from around $110,000 to $150,000 (Commercial Truck Trader

[13] The 2014 standards are not included in this analysis. First, this work does not find evidence of low-buy, and limited evidence of pre-buy, occurring in the one month prior to regulation. In addition, the increased capital costs expected from the rule are not clearly defined as there are a number of compliance pathways and are potentially offset by reduced operating costs due to improved vehicle efficiency. As such, further work would be needed to control for the effects of changing, and offsetting, operating costs in the elasticity estimation.

2020b; Cannon 2016) depending on vehicle specifications (e.g. power, sleeper cab, safety features, etc.). Class 7 trucks range from around \$80,000 to \$125,000 (Commercial Truck Trader 2020a).

As discussed in Section 4.4.2, significant pre-buy/low-buy effects for Class 8 trucks were observed for the 2004 regulations (low-buy in period 6 months post-regulation), 2007 (low buy 12 months post-regulation), 2010 (pre-buy 8 months, and low buy 2 months) and 2014 (pre-buy 1 month prior).

4.7.1 Cross Price Elasticity: Pre-Buy

The cross price elasticity of demand, or cross price elasticity (XED), measures the change in the quantity demanded of good A, in response to a change in price of good B, ceteris paribus. That is, we can use XED to measure the effect of post-regulation changes in price on pre-regulation purchases. For the purposes of this study, we may consider good A to be a pre-regulation HDV, and good B to be a post-regulation HDV. The cross price elasticity is given by

Equation 6

$$\mathrm{XED} = \frac{\%\ \Delta\ \mathrm{Quantity\ A}}{\%\ \Delta\ \mathrm{Price\ B}}$$

As described in Table 17, pre-buy is observed ahead of the 2010 regulations (combined period 8 months prior) and the 2014 regulations (1 month prior), with no pre-buy observed for 2004 or 2007 regulations. We focus on the 2010 regulations, as the 2014 regulations show statistically significant pre-buy in only the month prior to regulation. Furthermore, pathways for regulatory compliance with the 2014 regulations were variable, with firms adopting a combination of GHG mitigating technologies that would have led to both capital cost increases and fuel savings. As such, the change in price post-2014 regulation is challenging to quantify. We also do not present XED estimates for Class 7 trucks as there was no significant evidence for pre-buy during any of the pre-regulation periods, where increased capital costs post-regulation would be anticipated.

As no significant pre-buy coefficients were observed with the 2004 or 2007 regulations, the XED for those regulations is zero, i.e. anticipated price changes post-regulation have no effect on purchases prior to the regulation. We calculate the lower bound for XED for the 2010 regulations based on the significant pre-buy coefficient from the combined 8 months prior to the regulation ($\beta = 0.057$) and the price change based on the lower bound vehicle purchase price plus the expected cost of compliance. The upper bound is estimated using the largest pre-buy coefficient ($\beta = 0.105$) from the combined period 2 months prior to the regulation, and the upper bound HDV purchase price estimate plus the expected cost of compliance. HDV purchase price is adjusted to year of regulation prices based using the PPI-Trucks, as recommended by BLS. [14]

Table 18: Cross price elasticity of demand for pre-buy coefficient estimates (Class 8)

		Lower Bound			Upper Bound		
Year	Reg. Cost (2010$)	Period (Months)	HDV Price (2010$)	XED	Period (Months)	HDV Price (2010$)	XED
2004	$703	NA	$72,200	NA	NA	$98,400	NA
2007	$9,741	NA	$83,700	NA	NA	$114,100	NA
2010	$7,662	8	$91,600	0.681	2	$124,900	1.712

These results show lower and upper bound estimates for the XED of demand ranging from between 0.681 and 1.712, respectively. The signs on the XED estimates are positive and the estimates range from inelastic (XED < 1) to elastic (XED > 1). Positive XED values show the potential for substitution, with inelastic values showing partial substitution and elastic estimates showing substitutability. These XED estimates indicate that the goods are substitute goods, with pre-regulation HDVs potentially being at least partially substitutable for post-regulation HDVs. However, the period for which this substitutability applies is relatively short-lived, extending out to around 8 months prior to the date of regulation.

Importantly, there were also regulations, and periods pre-regulation, for which there were no significant coefficients on pre-buy. Therefore, while the lower bound is presented in Table 18 as the smallest significant coefficient over the largest change in price, we should also note that a cross-price elasticity of zero is feasible and should be considered.

4.7.2 Price Elasticity of Demand: Low-Buy

Estimating the price elasticity of demand (PED) allows for estimation of the effect of changes in price on HDV demand. As many regulations come with additional costs, estimating the potential effects of price changes is important for understanding regulatory impacts. The price elasticity of demand is given by the formula in Equation 7.

Equation 7

[14] https://www.bls.gov/ppi/ppiescalation.htm

$$\mathrm{PED} = \frac{\%\ \Delta\ \text{Quantity Demanded}}{\%\ \Delta\ \text{Price}}$$

As such, the percent change in the quantity of HDVs demanded is equivalent to the estimated coefficients in Section 4.4, and the percent change in price can be estimated using average estimates of vehicle purchase prices coupled with the incremental cost increases stemming from regulation.

Table 19 shows the results of price elasticity of demand estimates, derived from observed low-buy effects, for the 2004, 2007, and 2010 regulations. These estimates are based on reduced demand during the low buy period following regulation. The lower and upper bound estimates are derived using different inputs for both price and the coefficient on demand. The EPA cost estimates are used because they represent anticipated or estimated capital plus O+M costs, which were likely the best available information of potential cost increases available at the time. The adjusted vehicle purchase prices are estimated for the year of regulation using the lower and upper bound vehicle purchase price estimates ($110,000 and $150,000, respectively) adjusted using the PPI for heavy duty trucks (Figure 7), as recommended by BLS.

The lower bound estimates use the smallest (closest to zero) significant coefficient corresponding to the regulation. In 2002 (2004 regulations) the smallest significant β coefficient was -0.076 over the combined period 6 months post regulation (Figure 16) In 2007 the smallest significant β coefficient was -0.065 over the combined period 12 months post regulation (Figure 17) and in 2010 the smallest significant β coefficient was -0.075 over the combined period 5 months post regulation (Figure 18). The upper bound estimates use the largest (furthest from zero) significant coefficient corresponding to the regulation. In 2004 the largest β coefficient was -0.1148 over the combined period 3 months post regulation (Figure 16). Note that the coefficient for 3 months post 2004 regulations is non-significant. In 2007 the largest significant β coefficient was -0.149 over the combined period 6 months post regulation (Figure 17) and in 2010 the largest significant β coefficient was -0.144 (Figure 18) over the 1-month post regulation.

We do not present PED estimates for the 2014 regulations for two reasons. First, no statistically significant low-buy in response to post-regulatory price increase was observed. Second, compliance pathways with the 2014 regulations were many and varied. Firms could select from a series or combination of GHG mitigating technologies, which would have led to capital cost increases but reductions in operating costs through fuel savings. As such, the "cost" of the regulation could vary greatly across firms and in many cases lead to cost savings. We also do not present PED estimates for Class 7 trucks as there was no significant evidence for low-buy during any of the post-regulation periods, where increased capital costs would be expected.

Table 19: Price elasticity of demand for the 2004, 2007 and 2010 regulations (Class 8)

		Lower Bound			Upper Bound		
Year	Reg. Cost (Nominal $)	Period (Months)	HDV Price (Nominal $)	PED	Period (Months)	HDV Price (Nominal $)	PED
2002	$703	6	$72,200	-7.849	3	$98,400	-16.073
2007	$9,741	12	$83,700	-0.558	6	$114,100	-1.757
2010	$7,662	5	$91,600	-0.897	1	$124,900	-2.347

These estimates of the price elasticity of demand are best considered in context with a number of caveats. The β coefficients used to estimate elasticity of demand likely capture other aspects of the proposed regulations, not solely limited to changes in costs (i.e. the prices paid by firms). Other considerations may include technological concerns including the efficacy of the technology solution, as well as unintended consequences including adversely impacted fuel consumption and the reliability of untested control technologies. Furthermore, these elasticities are estimated over varying periods for the lower and upper bounds and between the two regulatory periods in order to best capture the range of significant coefficients estimated by earlier OLS models. Base vehicle prices and estimated regulatory costs are estimates and may not correspond directly with observed base prices or increased regulatory costs. Analysis of elasticities was performed on monthly data, and so it is reasonable to apply the estimated elasticities to monthly series. However, analysis of the coefficients over time indicates that the observed effects are short-lived, on the order of months rather than years, and as such should be considered in that context and not be more broadly applied to longer time periods. Though the coefficients may appear larger than other estimates in the literature, the period of effect is generally limited, and therefore the effects are likely smaller than if the coefficients were applicable for annual or longer scenarios.

With the above caveats considered, these estimates suggest elasticity of demand ranges from -0.558 to -2.347 for the 2007 and 2010 regulations. The 2004 regulations show a PED of 7.85 for the lower bound. While the upper bound estimate is included in Table 19, the coefficient used to calculate the PED value is not significant, and therefore we only include the PED estimate in the table for illustrative purposes. The expected compliance cost for the 2004 regulations is much lower than for the 2007 and 2010 regulations, which is one explanation for why the PED estimate is much greater for the 2004 regulations than for the 2007 or 2010 regulations. Importantly, for all regulations, we find evidence of coefficients that are non-significant, indicating that elasticities of zero, or no effect of regulation, are also suggested by the bounds of these results.

Note that though PED estimates are shown as negative further discussion ignores the sign, as is common when estimating and discussing PED. Depending on the combination of price estimates and regulatory costs, low-buy period and baseline vehicle costs used, the PED ranges from inelastic (PED < 1) to elastic (PED > 1). Lower bound estimates show inelastic demand for both the 2007 and 2010 regulations, while for the upper bound all estimates for PED are elastic. Again, as these are elasticities we can interpret the upper bound estimates as suggesting that a 1% increase in price corresponding to regulation would yield a 1.757% over 6 months to a 2.3% decrease over one month in Class 8 vehicle demand post-regulation. Time frame is important to consider as a smaller effect over a longer period of months may ultimately result in a larger overall effect. As such, these estimates suggest that a PED of 1.757 over 6 months post-regulation would represent the upper bound.

The 2004 regulations show highly elastic, albeit short-lived, price elasticity of demand. The high elasticity observed around the 2004 regulations is likely a function of two factors. First the cost of the 2004 regulations was low, both compared to other regulations, and to the purchase price of a new truck. Second, and arguably more important, the 2004 standards were implemented 15 months earlier than originally planned and introduced concerns regarding the reliability of the new engines, uncertainty which may have overshadowed the effects of increased costs and led to highly elastic PED estimates.

In instances where demand is inelastic the change in price, or incremental cost due to regulation, does not have a large impact on demand for that product. We see possible evidence of this for the lower bound of the 2007 and 2010 regulations when using the EPA cost estimates. Conversely, the upper bound estimates indicate elastic demand. When demand is elastic an increase in price leads to a proportionately larger change in demand, which in this instance may lead to substitution or other behaviors, i.e. low-buy effects, which are potentially detrimental to the efficacy of the regulation.

5 Conclusion

Heavy-duty vehicle activity is a major source of criteria pollutants in the transportation sector, contributing 35% more particulate matter emissions per year than light duty vehicles in the United States. The federal government has implemented a series of policies aimed at reducing pollution from heavy-duty vehicles which have cut particulate matter and nitrogen oxide emissions by 90% on a per unit activity basis since 1997. These regulations have led, and will continue to lead, to billions of dollars in estimated health and environmental benefits[15], but do not come without cost.

Pre-buy and low-buy behavior reduce the effectiveness of proposed regulations. Pre-buy is observed when heavy-duty vehicle buyers purchase more vehicles prior to the regulation than they normally might in order to avoid having to pay higher prices for regulation compliant vehicles . As such, the effect of the regulation is somewhat tempered as the vehicles purchased just prior to regulations are brand new and persist in the fleet after the regulation goes into effect.

Using sales data and time series econometric methods, this work identified some evidence of pre-buy and low-buy behaviors around regulations, especially for Class 8 trucks, as well as the potential for class-shifting, which has not previously been described in the literature. Small, short lived pre-buy effects were observed prior to the 2010 and 2014 regulations, though the 2014 pre-buy period was only one month. We observe low-buy in Class 8 sales for the 2004, 2007, and 2010 regulations, with the 2007 low-buy being the strongest and most persistent, leading to a ~15% decrease in monthly Class 8 sales for the period 6 months post-regulation. In general, low-buy and pre-buy effects were short-lived and were observed to diminish towards zero. In the case of the 2010 regulations, significant pre-buy and low-buy periods partially cancel one another out, though the period of significance was longer and larger for the pre-buy.

This study also identifies possible indicators of class shifting, which has not been previously discussed in the literature. We find evidence supporting conditions for possible class-shifting around the 2004 and 2010 regulations. In 2004 we see a small but significant increase in the ratio of Class 8 to Class 7 vehicles, but no significant increase in Class 8 sales on their own. This finding, taken together with a statistically significant observed decrease in Class 7 sales prior to regulation, are

[15] https://www.epa.gov/sites/production/files/2015-05/documents/2030annualbenefits.pdf

indicative of potential class shifting occurring ahead of the 2004 regulations. In 2010 we again see a statistically significant increase in the ratio of Class 8 to Class 7 sales, coupled with a short-run decrease in Class 7 sales. All else equal, these results are indicative of possible class shifting from Class 7 to Class 8 but importantly, they are not definitive, and do not explicitly demonstrate that class-shifting is occurring.

Finally, for Class 8 trucks we explore the cross-price elasticity for demand for pre-buy, and the price elasticity of demand during the post-regulation period, when anticipated costs are higher. In both cases low bound estimates were inelastic, indicating little change in purchasing behavior per unit price increase, while upper bound estimates were elastic. We find evidence of cross-price elasticities (where a significant effect is found) between 0.681 and 1.712 and price elasticities of demand between 0.558 and 2.347. These two sets of estimates are in good agreement and are best considered in the context of their time of significance. Pre-buy and low-buy effects are short lived, with the period of significance not extending beyond 8 months pre and post regulation. Importantly, these estimates of the price elasticity of demand and cross price elasticity are not based purely on the price. The estimated coefficients also likely capture unobserved aspects of the regulations, including technology uncertainty and performance and reliability limitations. As such, these estimates of price elasticity of demand and cross price elasticity represent upper bound estimates when accounting for other factors. In addition, as noted above, pre-buy and low-buy do not occur universally. These effects do not appear to show up in all rules, or for Class 7 vehicles. Thus, pre-buy and low-buy effects of zero are also reflected in the results.

These results are beneficial to EPA and regulatory agencies as they may be applied to help determine the magnitude of behavioral changes anticipated due to regulation. The duration of the effects observed are typically short-lived and as therefore duration is an important consideration when applying these results in the context of the magnitudes of the coefficients.

This report uses statistically rigorous and appropriate methods to identify short-term evidence of pre-buy and low-buy in the heavy duty freight sector. Pre-buy and low-buy elasticities, coupled with anticipated regulatory costs suggest mixed evidence that the relationship between regulatory cost and HDV purchases is elastic, again with only short-term effects. The findings of this report show that firms purchasing Class 8 vehicles sometimes engage in pre-buy and low-buy behavior around regulations, but the impacts are short-lived.

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7 Appendix

7.1 Cost of HDV Emission Regulations by Class

Table A - 1: Example Estimated Costs of HDV Emissions Regulations, 1988-2010, by HDV Class, Nominal and Real (2019$) Dollars

Standard Year, Pollutant and Source	**Description of Cost/ Nominal Dollars**	**Estimated Costs by HDV Class, Nominal**			**Estimated Costs by HDV Class, Real (2019$)**		
		LHDV/ LHDDE (HDV 2b-5)*	MHDV/ MHDDE (HDV 6 &7)*	HHDV/ HHDDE (HDV 8a & 8b)*	LHDV/ LHDDE (HDV 2b-5)*	MHDV/ MHDDE (HDV 6 &7)*	HHDV/ HHDDE (HDV 8a & 8b)*
1990 NOx (Reported as 1988, 6.0 g/bhp-hr) (U.S. EPA 1985)	Fuel costs, estimated lifetime increase for 1% fuel economy penalty, discounted ($1980)	$54	$259	$705	$133	$640	$1,741
	Fuel costs, estimated lifetime increase for 2% fuel economy loss, discounted ($1980)	$108	$518	$1,410	$267	$1,279	$3,483
1991 PM (U.S. EPA 1985)	Total User Costs Low (1984$)	$577	$901	$1,499	$1,425	$2,226	$3,703
	Total User Costs High (1984$)	$604	$1,030	$1,852	$1,492	$2,544	$4,575
1994, PM (U.S. EPA 1985)	First Costs (Purchase Price) (1984$)	$457	$535	$661	$1,129	$1,321	$1,633
	Fuel Economy Costs Low (1984$)	$54	$259	$705	$133	$640	$1,741
	Fuel Economy Costs High (1984$)	$81	$388	$1,058	$200	$958	$2,613
	Maintenance Costs (1984$)	$66	$107	$133	$163	$264	$329
	Total User Costs Low (1984$)	$120	$366	$838	$296	$904	$2,070
	Total User Costs High (1984$)	$147	$495	$1,119	$ 363	$1,223	$2,764
2004-2006 NOx (U.S. EPA 1997)	2004 Estimated Engine/Vehicle Costs (NPV** point of sale) (1995$)	$258	$397	$467	$433	$667	$784
	2006 Estimated Engine/Vehicle Costs (NPV point of sale) (1995$)	$224	$355	$411	$376	$596	$690
	2009 Estimated Engine/Vehicle Costs (NPV point of sale) (1995$)	$109	$136	$180	$183	$228	$302
	2004 Estimated Life-cycle Operating Cost Increase (1995$)	$7	$62	$131	$12	$104	$220
2007 -2010 (Sulfur/PM/NOx)	Projected Near-term (2007) Incremental Hardware Cost (1999$)	$1,990	$2,560	$3,230	$3,067	$3,945	$4,978

(U.S. EPA 2000)	Projected Near-term (2007) Incremental Operating Cost NPV (1999$)	$509	$943	$3,785	$784	$1,453	$5,833
	Projected 2009 Incremental Hardware Cost (1999$)	$1,601	$2,096	$2,618	$2,467	$3,230	$4,035
	Projected 2009 Incremental lifecycle Operating Cost NPV (1999$)	$509	$943	$3,785	$784	$1,453	$5,833
	Projected long-term (2012) Incremental Hardware Cost (1999$)	$1,170	$1,410	$1,870	$1,803	$2,173	$2,882
	Projected long-term (2012) Incremental Operating Cost NPV (1999$)	$537	$996	$3,979	$828	$1,535	$6,132

* As described by the U.S. EPA, HDVs are classified into the following categories: LHDDE, MHDDE, and HHDDE (Light, Medium and Heavy Heavy Duty Diesel Engine, respectively). LHDDE—Gross Vehicle Weight Rating (GVWR) of 8,500 to 19,500 lbs. and includes HDV classes 2b, 3, 4, and 5; MHDDE—GVWR 19,500 to 33,000 lbs., HDV classes 6 and 7; HHDDE—GVWR over 33,000 lbs., HDV classes 8a and 8b. Note that descriptions of classes (e.g. HDV, HHDDE, etc. and level of detail in use in EPA documentation (RIAs, etc.) have differed over time, and so may not necessarily align.

7.2 Class 6 Data

Table A - 2: Month of year seasonal effects for Class 6 sales

Month	Δlog Class 6
1	-0.0669*
2	0.0684***
3	0.1952***
4	-0.0876***
5	-0.0423
6	0.0255
7	-0.103***
8	0.0598*
9	-0.0963***
10	0.1058***
11	-0.1789***
12	0.1403***
Adj. R^2	0.275

Table A - 3 shows OLS regression coefficients for iterative model specifications for Class 6 trucks. Only model 2 shows any significant explanatory variables (GDP_{t-2}), and the coefficients on GDP are less robust to model specification, indicating that the macroeconomic factors affecting Class 6 sales may be different from those affecting Class 7 and 8 heavy duty truck sales.

Table A - 3: Iterative model specifications for class 6 trucks

	(1)	(2)	(3)	(4)
GDP_{t-2}	9.2531	10.2525*	6.8156	6.2763
Brent Oil_t		-0.0873	-0.0906	-0.0859
Total Imports and $Exports_t$			1.5275	1.5133
Consumer sentiment				0.2048
Adj. R^2	0.370	0.369	0.372	0.372

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Figure A - 1 shows evidence of pre-buy and low-buy behavior in the Class 6 sector, though only the one month pre-regulation ($p < 0.1$) and period two combined months post regulation ($p < 0.01$) are statistically significant.

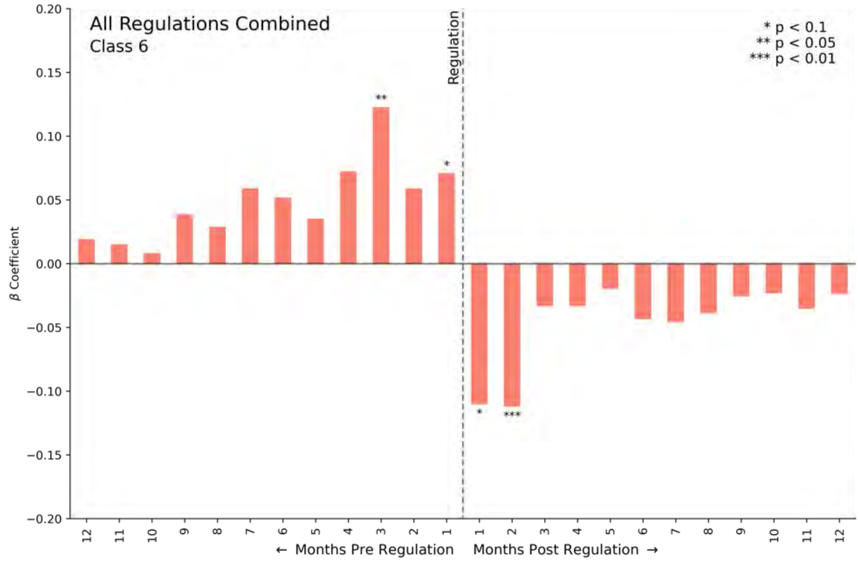

Figure A - 1: Pre- and post-regulation coefficients for combined months and regulations (Class 6)